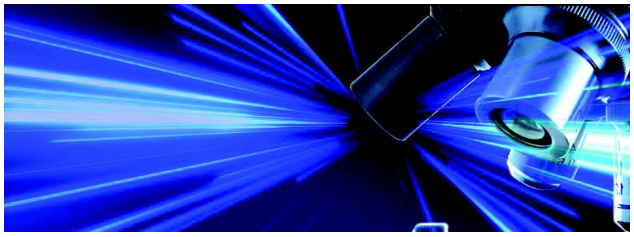
Proceedings

LASER 2014
Learning from Authoritative Security Experiment Results



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Message from the General Chair

Welcome to the 2014 Workshop on Learning from Authoritative Security Experiment Results.

Each year, LASER focuses on an aspect of experimentation in cyber security. The 2014 workshop focus was the science of cybersecurity, with a goal of improving the overall quality of practiced science. The event was structured as a workshop with invited talks and a variety of guided group discussions in order to best meet the overall workshop goals.

LASER 2014 sought research papers exemplifying the practice of science in cyber security, whether the results were positive or negative. Papers documenting experiments with a well-reasoned hypothesis, a rigorous experimental methodology for testing that hypothesis, and results that proved, disproved or failed to prove the hypothesis were sought. We also invited papers discussing promising research efforts that would benefit from expert feedback.

We received 12 submissions, which were each reviewed by at least three members of the Program Committee. The Program Committee accepted 2 full papers, which they believed reflected a rigorous, hypothesis-driven experimental approach to the problems and issues discussed. They additionally selected 3 papers that they believed would spur a good group discussion that would aid both the authors and workshop participants.

LASER recognizes that the future of cybersecurity lies with the next generation of researchers. As such, LASER sponsors students who are working to become researchers to attend and participate in the workshop. In 2014, two students received full sponsorship.

On behalf of LASER 2014, I wish to thank the many people who made this workshop possible:

- Our program chairs, who worked diligently to put together a strong technical program that would benefit the community
- The authors, who submitted papers to this workshop
- The members of the Program Committee, who carefully reviewed the submissions and participated in paper discussions
- Our organizing committee, who provided guidance and donated their time to handle everything from publicity to logistics to live webcasting
- The National Science Foundation, the CMU Software Engineering Institute CERT, and our other sponsors, who provided the funding and facilities necessary to make the workshop a reality
- The attendees, without whom there would be no workshop at all

We look forward to meeting everyone at LASER 2015!

Laura S. Tinnel, *SRI International*
LASER 2014 General Chair

Clusters and Markers for Keystroke Typing Rhythms

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Abstract

Background. People's blood comes in four types: A, B, AB and O. The markers for these blood types are the presence or absence of specific antigens. If people's typing rhythms – the unique pattern of someone's typing – can be similarly grouped into a small number of types, it could have forensic importance, allowing insider investigators to rule out a substantial fraction of suspects, just as Type-A blood rules out 60% of the population.
Aim. We aim to determine whether typing rhythms can be grouped into a small number (e.g., 3-10) of characteristic groups, and to find a marker that places a typist squarely into one group, as antigens do in blood typing.
Method. Data were 50 repetitions of a password (.tie5Roanl) from 51 typists. Agglomerative clustering elicited groupings in the data. Sparse logistic regression discovered the distinguishing characteristics of groups. A support vector machine identified specific markers.
Results. Three major groupings, or rhythm *types*, were identified, along with one singleton outlier. Preliminary work focused mainly on just one of these groups, whose members turned out to comprise all women. A Chi-Square test of independence determined that this was unlikely to have been a chance event ($\chi^2(df = 2, N = 50) = 13.1714, p < 0.005$). The singleton subject, an egregious outlier, suffered from a neurological disorder.
Conclusions. Typists can be grouped into a small number of types, as is done in blood typing. Markers can identify an individual as a member of a distinct type.

1 Introduction

Keystroke dynamics is the study of individual's typing rhythms, usually for the purpose of discriminating amongst different users. Most keystroke dynamics research has focused on the development of new classification algorithms to improve discrimination amongst users. Typically, researchers propose a new algorithm, gather a keystroke dataset, and evaluate the algorithm on this dataset. However, regardless of whether the results are better or worse than existing results in the literature, there is little understanding of *why* the algorithm performed better or worse. One reason for this dearth of understanding is the paucity of knowledge about the properties of keystroke data itself.

The field of keystroke dynamics is largely predicated on the fact that there is structure in the data; specifically, there is an assumption that different users generate different typing data. The differences can be used to distinguish between users. But this is not the only structure that exists. Users have various physiological and behavioral traits which may affect typing (e.g., gender, handedness, touch typist vs. hunt-and-peck, etc). Users with similar traits should produce similar data; such similarity may define a new aspect of structure in keystroke data.

Almost no research efforts have focused on understanding this additional structure. Bereft of this understanding, developers of new classification algorithms lack a guiding framework to improve classification accuracy. Instead of systematically exploiting this structure to improve accuracy, developers take a trial-and-error approach. This approach has not met with much success; most new algorithms are not markedly better than the simple algorithms proposed decades ago [8].

Our goal is to search for and quantify this additional structure in keystroke dynamics. We intend to establish a framework permitting future researchers to exploit this structure when developing new classification algorithms, whether for forensic, authentication, medical, or other purposes. We search a keystroke dataset for *clusters* – sub-groups of users that are distinct from the rest. We show that the clustered users share similar typing characteristics, which can be refined into *markers* for each sub-group. Markers are properties of a user's keystroke data that reliably identify the user as a member (or non-member) of a particular cluster, just as certain antigens classify a person as having a particular blood type.

2 Problem and approach

Our primary research question is: do people's typing rhythms fall into one of a few groups, or types? Ancillary questions ask whether these groups can be distinguished on the basis of their characteristic features, whether markers can be found that uniquely assign a user to a specific group, and whether any demographic traits are associated with the groupings, or types. Our approach comprises the following steps:

- **Find groupings in the data.** Groupings, or clusters, are found using agglomerative cluster analysis.
- **Discover distinguishing features.** Characteristics (features) of the data that distinguish members of one cluster from all other clusters or subjects are found with a sparse logistic regression classifier. This is an interpretable classifier which pinpoints specific characteristics unique to the users in a cluster.
- **Identify markers.** A Support Vector Machine (SVM) is used to create a table that rank-orders subjects by their median hold and latency keystroke timings. Users in the same cluster are ranked consecutively at the top of this table. A user is marked as a member of a cluster only if his rank lies below a particular threshold.
- **Associate clusters with demographic data.** User traits associated with clusters are found by matching cluster members against demographic information.

3 Related work

There are over 400 papers on keystroke dynamics (sometimes called keystroke biometrics or behavioral biometrics). None that we know of are relevant to grouping types of typing rhythms, but we can provide an overview of the field, as well as some pointed details, in the following paragraph. All of the cited survey papers generally treat keystroke dynamics as an authentication technique, but none unite the field's results into a pattern or theory of operation.

Peacock and his colleagues [11] provide a now somewhat-dated overview of the field, but one that is particularly accessible. Yampolskiy and Govindaraju [15] treat keystroke dynamics in the broader context of behavioral biometrics. Shanmugapriya and Padmavathi [13] give a short review of methods and metrics in keystroke dynamics. Karnan and his colleagues [4] give an overview of features and feature-extraction methods for keystroke dynamics, as well as a range of classification techniques. Banerjee and Woodard [1] provide a wide-ranging survey of the field, including the psychology of keystroke dynamics, data acquisition and environmental issues, and the usual list of technical approaches. Teh and his colleagues [14] provide a longer, more recent and broader-coverage review of the field, examining most of the same material as their predecessors, but including a longer and more recent list of cited papers.

Killourhy and Maxion have examined the influence of a variety of factors on the classification accuracy of keystroke dynamics classifiers, including the resolution of the clock used to perform keystroke timing [7], the definition of a successful login [9], and myriad other factors [6]. Their work parallels our present work. Whereas they focused on identifying and quantifying factors that affect classifier accuracy, we focus on finding identifying and quantifying structure in the keystroke data itself.

4 Data and data collection

We used a publicly-available dataset[1] whose key aspects are summarized below. Details of the experimental apparatus and instrumentation are given in [9]. Details of subject population, stimulus selection and experimental procedures are given in [7]. Human-subject trials were cleared by the CMU Institutional Review Board.

Subjects. 51 volunteers (30 male, 21 female), from a university population, contributed typing samples.

Apparatus. A Windows application on a PC (running the XP OS) prompted subjects to type the password. Typographical errors were discarded, and re-prompted, resulting in perfectly-typed repetitions of the password. Keystroke timings, taken with customized and calibrated hardware, were accurate to within $\pm$ 200 microseconds.

Stimuli. A 10-character string was used: .tie5Roanl followed by <return>.

Procedure. Subjects typed the 10-character string 50 times in each of 8 sessions, with at least one day between sessions. Total number of password repetitions was 400.

Demographic survey. Subjects provided demographic data, e.g., gender, age group, dominant hand, etc.

Data features. The data consist of *hold times* (the duration between pressing and releasing a key) and *latency times* (the durations between the release of a key and the depression of the next key). The hold and latency times are collectively referred to as *features*. Each repetition is treated as a *feature vector*, which consists of 11 hold times and 10 latency times.

Data set. The original data set [8] contained eight 50-repetition sessions for each of the 51 subjects. In the present work we use only the data from the eighth of 8 sessions, because that session is most representative of a subject's normal, practiced typing.

5 Step 1: Grouping the data

The first step in looking for groups in data is to cluster the data. This itself is a two-step process. First, the data need to be preprocessed into a form suitable for input to the clustering algorithm; then the clustering algorithm is run. We describe the preprocessing step first, to give readers some intuition about the form of the data; then we describe the clustering routine.

5.1 Method

We use the agnes clustering algorithm to find the groups [5]. Before applying the clustering algorithm, we preprocess each subject's multidimensional data so that they are represented as a single median vector.

Preprocessing. Before we can use a clustering algorithm, the input data must be preprocessed so that each of the 51 subjects is summarized in a single entity – a single vector. As previously mentioned, we have 50 repetitions of the password from each subject. Since we wish to consider each subject as a single item in the clustering algorithm, we summarize each subject by a single vector. To compress a subject into a single vector, we start by taking the median value, over all 50 repetitions, for each feature. This results in 11 median hold times and 10 median latency times. When concatenated, these 21 median times constitute a *median vector*. This process is repeated for each subject, resulting in 51 median vectors, one per subject. These 51 median vectors are then fed into the agnes algorithm.

Agnes clustering. Traditional clustering algorithms (e.g., *k*-means [3]) take some number of items to be clustered as input, and then output an assignment of each item to a single cluster. In our case, since we are interested in clustering subjects, the *k*-means algorithm will assign each subject to a single cluster. One major downside to these traditional clustering algorithms is that they often require the researcher to state the targeted number of clusters to be found (e.g., the k in k-means). When the number of clusters is unknown, researchers must use heuristic approaches to estimate the number of clusters that are present in the data.

Hierarchical clustering algorithms differ in that they return a hierarchy of clusters. Each subject will be a member of multiple hierarchical clusters. For example, a subject may be classified as a left-handed, female typist, as well as a left-handed typist, as well as a typist. Each successive cluster is more encompassing than its predecessor. Such hierarchical clusterings are often depicted as dendrograms, as shown in Figure 1. Unlike traditional algorithms, hierarchical clustering algorithms do not require the researcher to provide the targeted number of clusters as input; the clusters are derived automatically.

In this work, we use the agglomerative nesting clustering algorithm called Agnes [5]. This algorithm is an example of a "bottom-up" clustering, where each item is initially assigned to its own cluster. During iterations of the algorithm, clusters are merged together, until only a single, high-level cluster remains; this final cluster contains all items in the data set. More specifically, the algorithm is initialized by assigning each item to its own cluster. With each iteration of the algorithm, the two most similar clusters are merged. Similarity between two clusters is defined as the average Manhattan distance between all possible pairwise combinations of items in the two clusters. The algorithm iterates until all elements belong to the same, high-level cluster.

5.2 Results

Figure 1 shows the output of the agnes clustering algorithm, represented as a dendrogram, when applied to the 51 aforementioned median vectors. Nodes are labeled by subject number; red nodes are female.

A dendrogram visualization of a clustering is always a binary tree. Each child of the tree is either a cluster with a single subject (e.g., s002 at the far left), or a cluster that contains multiple subjects (e.g., the sub-tree containing both s002 and s020). The point at which two clusters merge is called a *junction*. For example, the first common junction of s002 and s020 represents the merger of those two subjects into a single cluster. The junction at height 38 (on the y-axis) represents the merger of two large clusters; all of the subjects are included in this cluster, excepting subject s036 at the far upper right.

The dissimilarity between any two subjects or clusters is proportional to the height (on the y-axis) of the first common junction that they share. For example, s002 and s020 (both on the left side of the dendrogram) are similar to each other since their first common junction has a low height, 16. However, s002 and s043 (on the extreme left and right sides of the dendrogram) are very distinct, because their first common junction is at height 38.

Four distinct clusters are visible in Figure 1: the "left cluster" containing s002 to s040; the "right cluster" containing s017 to s043; and the "middle cluster" containing all the rest of the subjects except s036, which is a singleton cluster at the far upper right.

In this paper we focus on only two of the clusters: the one containing only subject s036, and the one we called the "left cluster". A singleton cluster like s036 was completely unexpected. The "left cluster" happened to be all female subjects, again unexpected. For these reasons, and due to space constraints, we concentrate on these two clusters in the remainder of the paper. However, the techniques used from here on will generalize to any cluster or any individual subject.

6 Step 2: Discover distinguishing features

Having identified the four clusters into which the 51 subjects were grouped, we turn to the matter of determining which typing-rhythm features best distinguish one group (or, for that matter, one subject) from everyone else. Again we use a two-step process: the first is a data preprocessing step; the second, where the work is actually done, is sparse logistic regression.

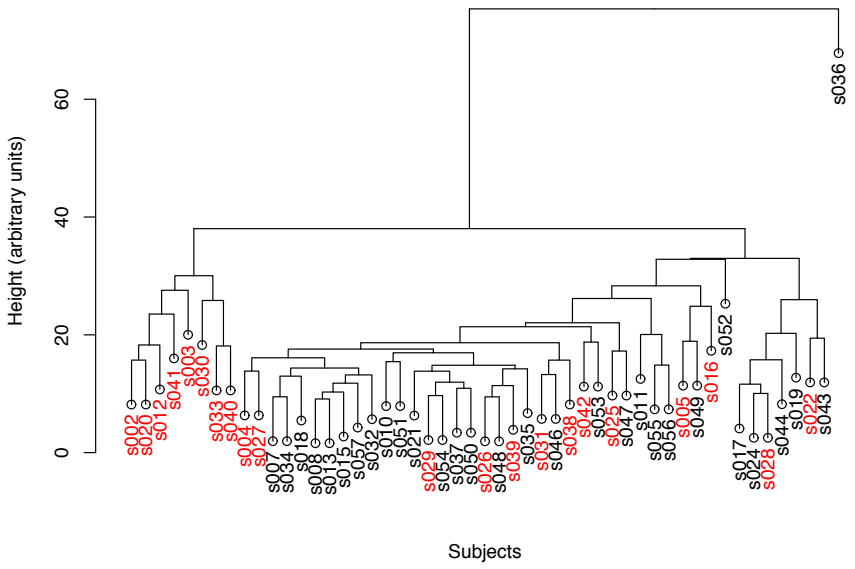

Figure 1: Dendrogram, based on session-8 median vectors, showing the hierarchical clusters of subjects produced by the agnes algorithm. Red subject numbers are female. Note the two clusters of interest: the "left cluster" of all female subjects at the far left, and the s036 singleton cluster at the far upper right.

6.1 Method

To identify the distinguishing features we use a sparse logistic regression classifier, the parameters for which are chosen via 10-fold cross validation.

Preprocessing. As a reminder, each of 51 subjects typed 50 repetitions of a password (.tie5Roanl). Each password contains ten characters plus <return>. The features are 11 hold times (the time a key is held down) and 10 latency times (the time taken to transition from one key to the next, from key-up to key-down). The typed text is preprocessed to represent the passwords as feature vectors, each of which contains the 11 hold times and 10 latency times, for a total of 21 features. The entire data set comprises 51 subjects x 50 repetitions = 2550 feature vectors. These feature vectors are provided as input to the sparse logistic regression classifier.

Sparse Logistic Regression. To identify distinguishing features that discriminate one user from others, or one cluster from the rest, we use a sparse logistic regression classifier. Since we will be directly interpreting the output of the classifier to identify distinguishing features, it is helpful to understand how the classifier operates. A typical logistic regression classifier takes n feature vectors (denoted $\mathbf{x}_i$ for $i = 1,...,n$) as input, along with a classification designation for each feature vector (denoted y_i for $i = 1,...,n$). In our case, we designate vectors belonging to subjects in the cluster with a '1' and vectors belonging to subjects not in the cluster with a '0'. The output of a logistic regression classifier is not only a classification of the feature vectors, but also a vector of weights, $\mathbf{w}$, which indicate the usefulness of each feature for the sake of accurate classification. This weight vector is the output of primary interest.

The logistic function is defined as

$$logistic(x) = \frac{1}{1+exp(-x)}$$

and the score is defined as

$$score = \mathbf{w} \cdot \mathbf{x} = \sum_{j}^{K} (\mathbf{x}_j \times \mathbf{w}_j),$$

where K is the number of features in each vector. With these definitions in mind, a logistic regression classifier assumes that the probability of a particular feature vector belonging to a subject in the cluster is:

$$P(y_i = 1|\mathbf{x}_i;\mathbf{w}) = logistic(\text{score}).$$

Of course, the classifier must actually choose $\mathbf{w}$. It does this through a maximum-likelihood approach. The likelihood function is given by:

$$\prod_i P(y = y_i|\mathbf{x}_i;\mathbf{w}).$$

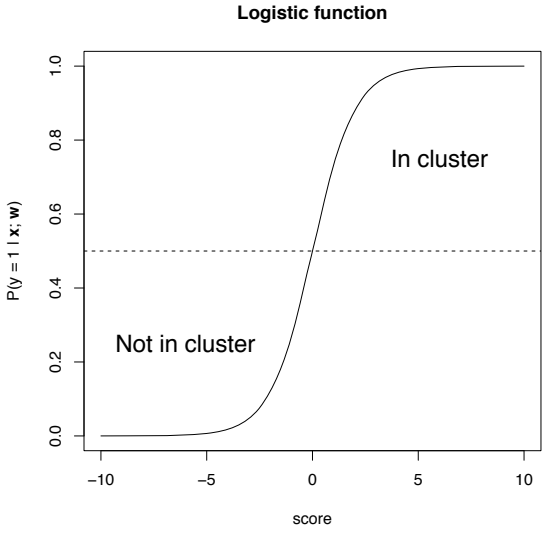

Figure 2: **Logistic function.** The logistic function converts any real-valued score into the probability that a feature vector belongs to a subject who is a member of the cluster. Vectors with a probability above 0.5 (dashed line) are classified as belonging to a subject in the cluster; points with a probability below 0.5 are classified as belonging to a subject that is not in the cluster.

Armed with the inner workings of the classifier, we can now gain an intuition about how the classifier operates. Figure 2 depicts the logistic function, which takes in any real-valued score as input and outputs a value between 0 and 1, which is interpreted as $P(y = 1|\mathbf{x};\mathbf{w})$, the probability that the feature vector $\mathbf{x}$ belongs to a subject in the cluster.

Note that the score of a feature vector is the sole determinant of whether it is labeled with a '1' or a '0'. A positive score will result in a feature vector being labeled as being from a subject who is in the cluster. Conversely, a negative score will result in a feature vector being labeled as being from a subject who is not in the cluster. The score is just the sum of terms; each term is the product between a weight and a feature value. The simple nature of the score makes it easy to interpret the information offered by the weights.

Consider any term in the score. The larger the magnitude of the term, the more influence it has on the final score and on the final label of the feature vector. If a term has a large magnitude and a positive sign, the label of the feature vector will be "pushed" towards '1'. If the term has a large magnitude and a negative sign, the label of the feature vector will be "pushed" towards '0'. A term will have a large magnitude if the weight has a large magnitude. Thus, features corresponding to high magnitude weights, regardless of sign, are important features because their terms have a large impact on the score.

At this point, it would seem that the most important features are those with the highest-magnitude weights. However, this is not necessarily the case. Keystroke features take on a wide range of values; latency times are sometimes an order of magnitude larger than hold times. Suppose that a latency time and a hold time have equal importance, and that the latency time is roughly 10 times greater than the hold time. In such a case, the hold time will receive a weight that is roughly 10 times that which was assigned to the latency time. Due to this bias, we cannot simply look for the highest-magnitude weights.

Rather, we examine the normalized weights, which are obtained by dividing each weight by the standard deviation of its associated feature. Weight normalization accounts for the bias in the weights. We can now interpret the normalized weights directly; the larger the magnitude of the normalized weight, the more important the feature.

Notice that we have been discussing a logistic regression classifier, not a *sparse* logistic regression classifier. We did this because the standard classifier is simpler to explain, and there is no difference in the interpretation of the weights generated by the two versions of the classifier. The sole difference between the two classifiers is the addition of an L1-regularization penalty to the likelihood of the sparse logistic regression classifier:

$$\prod_i P(y = y_i|\mathbf{x}_i;\mathbf{w}) - \lambda \sum_j^K |\mathbf{w}_j|,$$

L1 regularization uses a penalty term that encourages the sum of the absolute values of the parameters to be zero, making the model less complex, due to having fewer operative features. The magnitude of the penalty is controlled solely by the parameter λ. Its purpose is to cause unimportant features to have their weights set to 0, instead of a small number. The larger λ is, the more important a feature has to be to have a non-zero weight. The advantage of this penalty, and the advantage of the sparse logistic regression classifier, is that interpretation of the weights is easier since we need only focus on non-zero weights; all non-zero weights can be considered important, though their importance is still governed by the magnitude of the weight. The choice of λ is made via 10-fold cross-validation, discussed below.

For this work, we use an implementation of the sparse logistic regression classifier in the R statistical environment (version 2.15.2) [12], *glmnet* package [2].

Selection of λ via 10-fold cross-validation. As previously mentioned, the sparse logistic regression classifier has a single parameter, λ, which must be chosen. We choose this value through the use of 10-fold cross-validation. We start by selecting candidate values of λ. We use the default of the *glmnet* package, which chooses 100 candidate values of λ. The smallest candidate is

equal to 0.0001 times the smallest value of λ that would result in all weights being set to 0. Each successive candidate after the smallest is equal to 1.1 times the value of its predecessor (e.g., the second smallest candidate is 1.1 times the smallest candidate and the third smallest candidate is 1.1 times the second smallest candidate).

Next, we divide the data into 10 equally-sized partitions, called folds. For each candidate value of λ, 10 classifiers will be trained. Each classifier is trained on 9 of the 10 folds, and then tested on the remaining fold; each fold is chosen to be the test fold exactly once. The error rates of each of 10 classifiers are averaged to give an error rate for the candidate value of λ. This process is repeated for every candidate value. The chosen value of λ is the one that has the lowest average error rate.

Fitting the classifier. Prior to classification, the data are standardized so that each feature has zero mean and unit variance. The purpose of the standardization is to allow the sparse logistic regression classifier to view each feature equally.[2] Data from the cluster of interest (either s036 or "left") is labeled with a '1' and all other repetitions are labeled with a 0. Note that different classifiers are fit for the s036 and the "left" cluster. When fitting the classifier for s036, the repetitions from subjects in the "left" cluster are labeled with a 0. Similarly, when fitting the classifier for the "left" cluster, repetitions from s036 and other clusters would be labeled with a '0'. After the standardization and labeling process, cross-validation is used to select a value of λ. Finally, a classifier is fit with the chosen value of λ, using all of the data.

6.2 Results

We present results for two clusters: the s036 singleton, and the "left" cluster.

s036 Cluster. Table 1 shows the non-normalized and normalized weights produced by the sparse logistic regression classifier. For reasons previously discussed in Section 6.1, we use the magnitude of the normalized weights to determine the importance of features for discriminating between s036 and the remaining subjects.

We can see that the hold time on 'shift r', 'a', and 'n' are the most important features. There is a large gap between the magnitude of the weights on these three features and the next largest magnitude. Moreover, all three weights share a negative sign, indicating that small values of the features are indicative of s036. After the gap, the next most important feature is the latency time for 'n-l'. Its positive sign indicates that large values of that feature are indicative of s036.

In fact, these 4 features are sufficient to discriminate every single repetition of s036 from every repetition for any other user. All repetitions meeting the criteria below belong to s036. Any repetition that does not meet all 4 of these criteria belongs to some other subject.

Index	Feature	Weight	Normalized Weight
1	H.Shift.r	-137.71	-3802.45
2	H.a	-80.75	-2336.48
3	H.n	-67.38	-2178.82
4	UD.n.l	14.66	114.87
5	H.o	-2.93	-102.49
6	UD.Shift.r.o	9.96	63.89
7	UD.l.Return	9.90	55.95
8	UD.o.a	4.98	55.80
9	UD.a.n	3.93	43.91
10	UD.i.e	4.52	40.95
11	UD.period.t	2.42	14.50
12	UD.e.five	0.65	3.29
13	H.l	-0.01	-0.30
14	UD.five.Shift.r	0.05	0.23
15	H.period	0.00	0.00
16	H.t	0.00	0.00
17	H.i	0.00	0.00
18	H.e	0.00	0.00
19	H.five	0.00	0.00
20	H.Return	0.00	0.00
21	UD.t.i	0.00	0.00

Table 1: **Sparse logistic regression weights: s036.** The normalized weights (right column) with the highest magnitudes correspond to the features with the most influence on correctly separating s036 from all other subjects. "H" indicates hold time; "UD" indicates key-up to key-down interkey latency time.

1. Hold time for 'R' is less than 60 milliseconds
2. Hold time for 'a' is less than 80 milliseconds
3. Hold time for 'n' is less than 60 milliseconds
4. Latency time for 'n-l' is more than 40 milliseconds

"Left" Cluster. Table 2 shows both non-normalized and normalized weights that were produced by the sparse logistic regression classifier. For reasons previously discussed in Section 6.1, we use the magnitude of the normalized weights to determine the importance of features for discriminating between subjects in the "left" cluster and the remaining subjects.

One notable difference between the weights for the "left" cluster and the weights for the s036 cluster is that all of the "left" cluster weights are non-zero. The lack of zero weights indicates that all features are of at least some importance in discriminating between members of the "left" cluster and all other subjects.

Note that the weights associated with hold times are almost always positive, indicating that longer hold times are indicative of subjects in the "left" cluster. Weights

	Feature	Weight	Normalized Weight
1	H.i	92.45	3105.03
2	H.period	94.37	2843.08
3	H.a	89.98	2603.60
4	H.o	52.59	1842.87
5	H.l	44.29	1562.09
6	H.e	50.57	1343.99
7	H.n	25.55	826.16
8	H.Return	20.89	697.19
9	H.t	9.71	325.05
10	H.five	6.69	301.88
11	H.Shift.r	-8.80	-243.03
12	UD.t.i	7.15	79.79
13	UD.a.n	6.43	71.82
14	UD.l.Return	5.66	32.00
15	UD.i.e	-3.27	-29.57
16	UD.o.a	2.22	24.86
17	UD.Shift.r.o	-2.11	-13.54
18	UD.e.five	2.61	13.21
19	UD.period.t	0.91	5.44
20	UD.n.l	-0.65	-5.12
21	UD.five.Shift.r	-0.50	-2.13

Table 2: **Sparse logistic regression weights: "Left".** The normalized weights (right column) with the highest magnitudes correspond to the features with the most influence on correctly separating the subjects in the "left" cluster from all others. "H" indicates hold time; "UD" indicates key-up to key-down interkey latency time.

associated with latency times show no tendency to be either positive or negative, so no particular conclusions can be drawn.

7 Step 3: Identify markers

Thus far, we have accomplished two of our initial aims. We have identified clusters of subjects in our data, and we have identified features that distinguish them from the remainder of the subjects. We now turn to summarizing a large group of features into a single marker.

7.1 Method

We first introduce the concepts of average hold and latency-time rankings, and then refine these rankings further with the use of a Support Vector Machine (SVM).

Average hold and latency-time rankings. In identifying the important features for discriminating between subjects in a cluster and subjects outside a cluster, we noticed that both classifiers (one for the s036 cluster and the other for the "left" cluster) identified important hold-time and latency-time features. In an attempt to refine these features down to a marker, we determined that a rank-ordering of the subjects, from longest hold/latency times to shortest hold/latency times, might allow us to define a simple marker.

We start our discussion with a rank-ordering of subjects by their hold times. For each subject, we compute the *average hold-time ranking* as follows:

1. Choose a single hold time for a single feature.
2. For each subject, compute the median value for that hold time for that subject.
3. Rank the subjects from the largest hold time (rank 1) to the smallest (rank 51).
4. Repeat this process for each hold time, producing 11 rankings for each subject.
5. Average the 11 rankings to produce the average hold-time ranking.

A subject that always has the longest hold time would have an average rank of 1, while a subject that always has the shortest hold time would have an average rank of 51 (as we have 51 subjects). An analogous process produces the *average latency-time ranking*; the difference is that there are 10 latency times as compared to 11 hold times. Tables 3 and 4 show a portion of the average hold-time ranking and the average latency-time ranking tables.

Support Vector Machine (SVM). In an ideal world, either the average hold-time rankings or the average latency-time rankings would suffice as a marker. One would hope that all subjects inside a cluster would be consecutively listed on at least one of the two tables. In such a scenario, the marker for a cluster would be an average hold-time (or latency-time) ranking between some upper and lower limits. Unfortunately, this is not always the case. Sometimes neither table lists cluster members consecutively. In such a case, we wish to form a combined ranking that *does* create such a consecutive list.

To ensure that the results are still easily interpretable, we would like to create a combined ranking using a linear combination of the two rankings: combined ranking = A $\times$ average hold-time ranking + B $\times$ average latency-time ranking. Having decided on a linear combination, the only task left is to choose the two-element coefficient vector which is comprised of A and B. So far, our only stated goal is to have all subjects in a cluster listed consecutively when sorted by the combined ranking. To simplify this further, we can insist that all subjects inside the cluster must have a combined ranking below some threshold, while all other subjects must have a combined ranking above that threshold. That is, when using this combined ranking, we ask that subjects inside the cluster are separated from subjects outside the cluster.

There may be many coefficient vectors, however, that produce a combined ranking with the desired separation property. Therefore, we need to have some criterion as

a basis for deciding which vector to pick. A natural approach would be to select a vector that separates subjects inside and outside the cluster by the largest possible margin. The margin is the minimum distance between the combined score of any subject inside the cluster and the combined score of any subject outside the cluster. This approach, though, is still not perfect. Suppose that some pair of A and B creates a margin of 1; then the pair 10A and 10B creates a margin of 10. To get around this scaling issue, we add one final condition: the coefficient vector must have unit length.

This problem formulation is the same formulation that underlies a Support Vector Machine (SVM) using a linear kernel. In particular, an SVM will take two items as input. The first is the average hold-time ranking and average latency-time ranking for each subject. The second is a label indicating whether each subject is inside the cluster or not; subjects inside the cluster will be labeled with a '1' and subjects outside the cluster will be labeled with a '0'. The SVM will output two coefficients, A and B, that provide the largest margin of separation.

7.2 Results

Tables 3 and 4 show a portion of the average hold-time ranking and the average latency-time ranking tables, respectively. The first column in each table contains the position of each subject (2nd column) according to the average hold/latency-time ranking (3rd column). The fourth column shows the median hold/latency time in milliseconds, to provide the reader some context of the time scales at play. Some subjects omitted for brevity.

s036 cluster. Subject s036 stands out quite clearly in both the average hold-time and latency-time ranking tables. He has the lowest average hold-time ranking out of all the subjects, indicating that he has consistently short hold times overall. He also has the highest average latency-time ranking, so he has consistently long overall latency times, too. Since he is already well separated from all other subjects, there is no need to apply an SVM.

There are several possible markers that we can choose for s036. One marker is that the subject must have an average hold-time ranking above 48. Another would be that the subject must have an average latency-time ranking below 3. A third marker would be to insist that both these criteria hold simultaneously. Any of these choices of marker would cleanly separate s036 from all other subjects or clusters. Note that in actually using the marker, no additional classification needs to be done. The mere presence of, say, an average hold-time ranking above 48 is enough to separate s036 from everyone else. That's the benefit of having a marker.

"Left" cluster. The subjects in the "left" cluster all have a high average hold-time ranking. However, this separation is not perfect. As can be seen in Table 3, subject s011 has a ranking of 12.82. This is between the rankings of subjects s040 (rank 11.64) and s030 (rank 13.09). Unfortunately, s011 is not in the "left" cluster while subjects s040 and s030 *are* in the cluster. Looking at Table 4, we can see that the subjects in the "left" cluster have wildly varying latency-time rankings.

Position	Subject	Hold-time Ranking	Median hold time (ms)
1	**s041**	**3.09**	**157.40**
2	**s012**	**4.64**	**135.25**
3	**s003**	**4.82**	**143.50**
4	**s033**	**6.55**	**132.05**
5	**s002**	**8.00**	**124.75**
6	**s020**	**8.82**	**122.50**
7	**s040**	**11.64**	**117.50**
8	s011	12.82	114.05
9	**s030**	**13.09**	**113.00**
10	s056	15.82	104.75
...	...	...	....
...	...	...	....
50	s024	46.55	57.60
51	*s036*	*49.55*	*50.70*

Table 3: Average hold-time ranking for each subject. Subjects in the "left" cluster are in boldface. Because s011 (not in "left" cluster) is ranked higher than s030 (in "left" cluster), the table shows that average hold-time ranking is an imperfect marker for membership in the "left" cluster. Subjects in positions 11-49, not relevant here, are omitted for brevity.

Position	Subject	Latency Ranking	Median latency time (ms)
1	*s036*	*2.00*	*437.40*
2	s022	5.00	255.65
...	...	...	...
...	...	...	...
7	**s030**	**12.30**	**143.60**
11	**s033**	**16.40**	**159.35**
13	**s040**	**17.00**	**173.65**
25	**s002**	**24.90**	**63.10**
33	**s020**	**28.80**	**70.00**
38	**s041**	**36.50**	**52.35**
48	**s003**	**43.50**	**3.90**
51	**s012**	**44.60**	**11.05**

Table 4: Average latency ranking for each subject. Subjects in the "left" cluster are presented in boldface. The subjects in the "left" cluster are not grouped by position in the table; hence latency-time ranking is not a good marker by itself. Many subjects are omitted for brevity.

Position	Subject	Hold Ranking	Latency Ranking	In cluster?	Combined Ranking
1	**s033**	**6.55**	**16.40**	**1**	**10.20**
2	**s041**	**3.09**	**36.50**	**1**	**11.55**
3	**s002**	**8.00**	**24.90**	**1**	**13.61**
4	**s003**	**4.82**	**43.50**	**1**	**14.87**
5	**s012**	**4.64**	**44.60**	**1**	**14.95**
6	**s040**	**11.64**	**17.00**	**1**	**15.29**
7	**s020**	**8.82**	**28.80**	**1**	**15.32**
8	**s030**	**13.09**	**12.30**	**1**	**15.61**
9	s005	16.36	15.30	0	19.49
10	s016	20.91	10.30	0	22.74
11	s011	12.82	44.30	0	22.83

Table 5: SVM Ranking. Subjects in the "left" cluster (bold) are perfectly separated from the rest. Subjects are sorted by the combined ranking, which is computed as Combined Ranking (e.g., 10.20 in row 1) = 0.9722 × Hold Ranking + 0.2341 × Latency Ranking. Subjects after position 11 are omitted for brevity.

Since our goal is to obtain a marker that perfectly separates the "left" cluster from all other subjects, we take the SVM approach. Table 5 shows the results. The SVM chose 0.9722 as the coefficient for the average hold-time ranking and 0.2341 for the average latency-time ranking. Using these coefficients, the combined ranking can be computed (right-most column of Table 5). This combined ranking can be used as a marker to perfectly discriminate between members of the "left" cluster and all other subjects. All members of the "left" cluster have a combined ranking of less than 17, while all other subjects have a combined ranking of at least 17.

8 Step 4: Demographic association

After identifying two noteworthy clusters in the data, a natural question to ask is whether the subjects in these clusters share common characteristics.

8.1 Method

We did a simple correlation between a modest data base of demographic characteristics (gender, handedness, age, special conditions) and the subjects in the clusters. Two associations were found: gender and special conditions.

8.2 Results

s036 cluster. This subject suffered from temporal lobe epilepsy, a neurological disorder. Medication for epilepsy can affect fine motor control, which may explain the very short hold times and very long latency times observed in the s036 data.

"Left" cluster. The only association between demographic data and the subjects in the "left" cluster was gender. All the subjects in the "left" cluster were women.

A Chi-square test of independence was performed to examine the relation between the "left" cluster and gender. The relation between these variables was significant, $\chi^2(df = 2, N = 50) = 13.1714, p < 0.005$. That all the subjects in the "left" cluster were female is highly unlikely to have been a chance event. A Bonferroni correction [10] for multiple comparisons is probably unnecessary, but if one were applied, given an alpha of 0.05, and four comparisons, the p-value would need to be less than 0.0125 to maintain significance, which it is. We don't know what unites these women. Perhaps it's fingernails; perhaps it's nail polish; perhaps it's hand size or hand geometry. We have neither the data nor the instrumentation to make a determination at this time.

9 Discussion

We have demonstrated that a 3-step process can reveal a small number of types into which typists can be grouped, just as there is a small number of blood types in which all people are included. Also, as in blood typing, we have shown that markers can be found that make exact assignments of typists to clusters, obviating the need for re-clustering data when new subjects appear. We found that one subject, all alone in one singleton cluster, suffered from a neurological disorder, temporal lobe epilepsy. An 8-member cluster was made up entirely of women; as yet we have no explanation for what unifies these women.

The clusters into which subjects are grouped constitute new-found, fundamental structure in keystroke data, heretofore unknown. These clusters show that there appear to be constellations of characteristics that unite subjects into some groups, while isolating them from others. Demographic correlations may shed further light on these groupings or structures in the data. Extended demographic data, information about typing postures (e.g., particular hand positions), and details regarding the tendency to strike a given key with a given finger are needed to take full advantage of the new structure. With these kinds of details we may now be able to determine more than a typical classifier can do; typical classifiers tell you that two entities are different, but they don't tell you *how*

they are different. The discovery and use of new structure is a step toward resolving that problem.

We have provided a way to rule out people on the basis of their typing rhythms. For example, if an unidentified pedophile's typing fell into a particular cluster, based on monitoring of chat-room typing, the authorities would know that they are looking for only one "type" of typist, and could rule out others. The situation would be similar in other forensic applications, such as insider threat.

Classification accuracy in keystroke biometrics may improve on the basis of the new-found structure. In keystroke research it is typical to discriminate amongst a pool of users by running a classifier over the entire pool, which produces a certain classification accuracy. If the same classifier were run over just *one cluster* of that pool, classification accuracy may well improve, because the pool is smaller; and the distinction between that pool and the rest of the users would already have been made by the clustering algorithm itself. Moreover, it's possible that different classifiers will be differentially effective when applied to one cluster rather than another.

10 Limitations

The work presented in this paper is only a preliminary investigation, leaving many stones unturned. We examined only one data set; generalization to other data sets remains to be verified. We examined in detail only one cluster ("left") and one singleton (s036), leaving out marker-finding for other clusters; this is because our work here is intended as simply a proof of concept. Exploiting the new-found structure to increase classification accuracy is left to future work. Subsequent investigations will clarify these limitations.

11 Conclusion

We have shown that typists can be grouped into a small number of types. Each type is distinguished from the rest of the population by characteristic keystroke features, which can be refined into simple markers. A user's type is determined by the presence of these markers, in the same way that blood types are determined by the presence of certain antigens. Our findings constitute an initial step toward a more fundamental understanding of the intrinsic structure in keystroke data. We hope that other investigators will continue down this path by applying our techniques to various publicly available data sets.

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Notes

[1] Dataset available at `http://www.cs.cmu.edu/~keystroke`

[2] We compare normalized weights when we are standardizing the input data, because the *glmnet* package returns weights on the original scale, effectively "un-normalizing" the weights.

Text Entry Method Affects Password Security

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Abstract

Background. Text-based passwords continue to be the primary form of authentication to computer systems. Today, they are increasingly created and used with mobile text entry methods, such as touchscreen qwerty keyboards, in addition to traditional physical keyboards.
Aim. This paper aims to answer a foundational question for usable security: whether text entry methods affect password generation and password security.
Method. This paper presents results from a between-group study with 63 participants, in which each group generated passwords for multiple virtual accounts using different text entry methods. Participants were also asked to recall their passwords afterwards.
Results. One-way ANOVA across groups was performed on metrics including password length, amount of different characters, and estimated password security. The results showed significant effect of text entry methods on the amount of lowercase letters per password across groups ($F(2,60) = 3.186$, $p = .048$, $\eta_p^2 = .066$), and non-significant effect on the password length, amount of uppercase letters, digits or symbols. No significant result was found for the estimated password security. The result of practical cracking attacks was also similar across groups.
Conclusions. Text entry methods have effect on password security. However, the effect is subtler than expected.

1 Introduction and Background

Text-based passwords remain as the most prevalent method of authentication [1]. In addition to traditional computers such as desktops and laptops, people increasingly generate and use passwords with a wide variety of mobile terminals, such as tablets and smartphones. These mobile terminals have very different text entry methods compared to traditional computers. The appearance of such text entry methods drastically diversified how we use password authentication.

Mobile terminals are also replacing traditional computers in daily tasks. For example, Pew Research estimates that 21% of all US adult cell phone owners use primarily their phone to access the web [2].

A *text entry method* [3] consists of those physical (e.g. form factor, display, etc.) and software (e.g. virtual keyboard layout) aspects of an input device that are relevant when entering text. The design of a text entry method determines how quickly and effortlessly a given character can be typed. Even small changes in how characters are displayed and organized can affect typing performance [4]. As a result, experienced typists on physical keyboards reach more than 60 words per minute (wpm) [5], whereas tablets and smartphones are in the range of 20 to 30 wpm [6,7]. Further, one should see corresponding differences in the distribution of characters in different methods. For instance, digits are not directly reachable without changing the layout in the common touchscreen qwerty keyboard on smartphones – does this affect the generated passwords?

2 Aim

In the present study, we examined whether the design of text entry methods affected the security of generated passwords. We hypothesized that, depending on password generation strategy, users may generate passwords using the characters on the display as generation cues. More precisely, the difficulty to reach a character from the present layout should affect the probability of its inclusion in a password. This could manifest both password structure and password security. Therefore, we aimed at discovering possible difference in both password structure and security.

We first examined whether structure of generated passwords. Metrics of password structure included password length, the amount of lowercase letters, uppercase let-

ters, symbols and digits per password. We also looked at types of passwords. We defined the type of a password by types of characters it contained.

Second, we explored the question whether text entry methods affected password security. We estimated security of passwords from two aspects: quantitative estimation and practical cracking attacks. Quantitative estimation included Shannon entropy [8, 9], NIST entropy [10] and a recently introduced Markov-model-based metric (adaptive password-strength meter [11]). Then we looked at was how resistant passwords were against cracking attacks. We issued both dictionary attacks and rule-based guessing attacks.

Finally, we studied if participants perceived the task with different text entry methods differently using NASA Task Load Index assessment (TLX) [12].

3 Related Work

In this section, we first focus on what is known about generating passwords with mobile text entry methods, and then password generation in general.

Researchers have studied usability of mobile platforms for passwords. Greene et al. [13] studied the difference between typing passwords using tablet and smartphone in a between-group experiment. The time used for participants to type and recall passwords were significantly different provided with different entry methods. They were also different given different passwords. Schaub et al. [14] found similar significant difference among different smartphones. In addition, they found that attackers had significantly different success rates in shoulder surfing passwords on different smartphones. Both of mentioned studies did not ask participants to create passwords, and provided participants passwords instead, thusly having little information on password generation and consequently how password security would be affected if created using different entry methods.

Few studies have specifically looked at helping people to create passwords on mobile text entry methods. Haque et al. [15] have studied how to create better passwords on mobile devices. They found entropy of passwords were significantly different across mobile keyboards. However, only an approximation of Shannon entropy was examined. An analysis with other security metrics and also password structures could help us gain more insight on the effect of text entry methods. Jakobsson et al. [16] proposed fastwords, which relied on standard error-correcting features for users to create passphrases.

Florencio et al. [17] have studied web password habits in a large scale. They found that most people managed multiple passwords, and their passwords were generally of poor quality, and were re-used and forgotten frequently. Grawemeyer [18] conducted a diary study and found people had different strategies for different accounts. Such studies indicated that multi-account scenario would be reasonable in password experiments.

Recently, Bonneau et al. [19] studied how people chose 4-digit PINs for banking cards. Common strategies included birth dates and visual patterns. The reported presence of visual strategies supported our hypothesis that password generated with different text entry methods, too, may differ.

Researchers have also studied how password generation policies affected password security. Weir et al. [20] claimed that passwords created under common requirements, such as minimum length and different character set requirements, were still vulnerable to cracking attacks. Shay et al. [21] found that some policies that required longer passwords provided better usability and security compared with traditional policies. Ur et al. [22] found that stringently rated password meters led users to make significantly longer passwords that included more types of characters, and passwords were also more resistant against cracking algorithms. However, Egelman et al. [23] showed that password meters helped little if people considered the accounts unimportant.

Therefore, specific policies and requirements do affect password generation and security. To exclude such effect from our experiment, one might need to avoid explicit password generation requirements.

Finally, Fahl et al. [24] compared real passwords to those generated in an experiment, finding that about 30% of subjects do not behave as they do in real life. However, the authors concluded that laboratory studies generally created useful data.

4 Method

Our study was conducted in a laboratory to control for confounding factors. A controlled laboratory experiment allowed for choosing the main factor to be considered, in our case the text entry method. Next, we describe our method in details.

4.1 Experiment Design

The experiment followed a between-group design with text entry method type (3 levels) as independent variable.

We divided our participants into three groups based on text entry method variable. The participants were randomly assigned into one of these three groups, and were unaware of the assignments or that other groups existed. A detailed explanation for the differences between groups was given in the next subsection.

The main reason for us to choose between-group was to isolate its effect from any other undesired effects such as any possible confounding factors that would correlate

with both the variable and the result. We noticed that previous work that involved password generation process also had similar experiment design [13, 14, 25].

An alternative design would be within-subject, in which one participant would perform the same task using three different text entry methods in a sequence. In such design, the use of different text entry methods would generate undesired interference to each other for each participant. In particular, learning and using one text entry method would interfere with the learning and using of other text entry methods, thus decreasing or even eliminating the potential effect of both methods. Such interference is common in paired tasks [26, 27].

Florencio et al. revealed that people manage multiple passwords in reality [17]. To increase ecological validity, we asked participants to manage three different virtual accounts. However, since the difference within each participant was not in our research objective, we did not analyze the difference among three passwords created by each participant. Instead, mean value of three accounts was taken to represent each participant in our models.

4.2 Apparatus

Our text entry method variable was defined by the apparatus each group used.

Laptop group (control group)

We provided a common laptop (Macbook Pro 2012 with a 13" display) in the laptop group. We chose so because the physical laptop keyboard was still the most common text entry method for password creation.

Tablet group

We provided Samsung Nexus 10 tablet (Android 4.2.2, 10.1" touchscreen) as the device used in tablet group. The touchscreen keyboard on the tablet had a common qwerty layout, as shown in Figure 1. Given that the tablet can be held in the hands in two ways, we asked the participants to keep it in the "landscape" mode.

Smartphone group

We provided a Samsung Galaxy Nexus (Android 4.2.2, 4.5" touchscreen) as the device used in the smartphone group. The keyboard layout was chosen from several available designs for smartphone platforms.

The difference between our smartphone keyboard and tablet keyboard was the number of key presses needed to reach certain keys (see Figure 1). To reach uppercase letters, one needed to press two additional keys from the first layout in smartphone group, while only one key press in tablet group. Also, to reach special symbols layout, three additional key presses were needed in smartphone group while only two in tablet group. In short, reaching certain keys and switching layouts demanded more effort in smartphone keyboard than tablet keyboard. The primary reason we chose our text entry methods so was to differentiate each group in their difficulty of reaching keys during text entry. All three apparatus still provided common usability for the particular platform.

Software

The application was implemented in both Python (for laptop group) and Java for Android (for smartphone and tablet group). It had mainly two features: password creation and password recall. In the password creation interface, participants were asked to create usernames and passwords for three virtual accounts in the same order. Each virtual account had a different logo, color and short description. In the recall interface, it asked participants to recall what they created earlier for each account, in a different order. "Give up" button would show up after four failed attempts for each account.

4.3 Procedure

All experiments were conducted in the same office room we setup for this study.

The primary task for participants was to create and recall username and password for three different types of virtual accounts. We minimized the risk for participants by advising them not to use their existing passwords, and also keeping data in a safe place.

Our study consisted two sessions. In session one, we asked participants to create a username and a secure password for three different accounts given a certain text entry method. The detailed procedure was as follows:

1. **Introduction to the Study**. The participants were introduced to the study, which included reading and signing the consent form, discussion of their rights and also compensation.

2. **Password Creation**. Each participant was given the corresponding text entry method before the session. They were asked to create usernames and passwords for three different virtual accounts: bank, email and online magazine. The order of the accounts was the same for all participants at this step.

3. **Subjective Workload Assessment** The participants were asked to fill out the NASA TLX form [12].

4. **Distraction**. The participants were asked to do a mental rotation task [28] and count down from 20 to 0 in mind.

5. **Password Recall**. Participants were asked to recall usernames and passwords they created in the Password Creation step above. The order of the accounts were changed with Latin square. For each account, participants were allowed to try as many time as

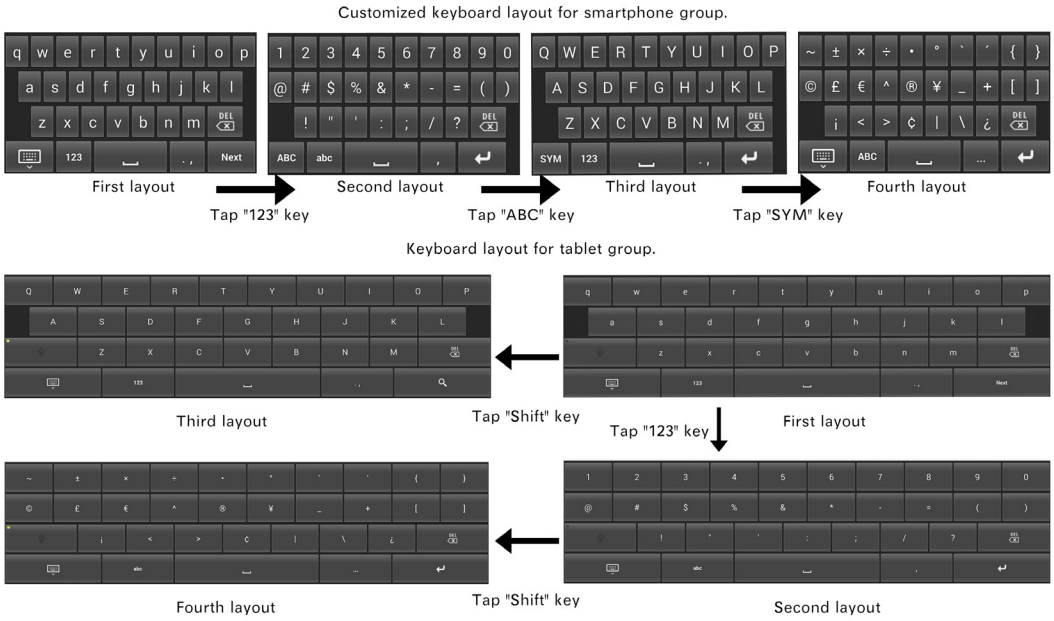

Figure 1: The keyboard layout for the devices in tablet group and smartphone group. Note two groups shared the same key positions within each layout, but the structures of the four layouts were different for them: tablet group followed the more common structure, while smartphone group had a hierarchical structure. To reach the next layout of smartphone keyboard, one had to first reach the previous one. Therefore, smartphone keyboard had a higher difficulty reaching non-lowercase keys than tablet keyboard.

they wanted, and give up if necessary (showed up after four failed attempts).

6. **Survey**. Participants were asked several questions about password generation and also usual demographic questions.

In session two of our study, which was at least 10 days after session one, participants were asked to come back to recall the usernames and passwords again. The recall procedure was the same as that in session one. After the recall process, participants were asked to fill out NASA TLX form and answer a few questions. We included recall sessions so that to avoid participants creating unrealistic passwords if they knew they would not need to recall passwords afterwards.

4.4 Participants

We recruited participants through fliers, mailing lists, and in person at cafeterias. Participants were required to be over 18 years old and familiar with touchscreen devices. We recruited 63 participants in total, between the ages of 18 to 65 ($M = 27.2, SD = 9.9$). 24 of our participants were male and 39 were female.

All 63 participants completed session one of our study, and 57 of them returned for session two. As compensation, participants received one $30 gift card each for completing the whole study. They also participated in a raffle of three $75 gift cards.

We recruited our participants in two batches, 33 in May and 30 during June and July 2013. The gap between two sessions of the study varied. The mean time gap for the first batch was 14.53 (SD = 5.81) days and 29.52 (SD = 7.57) days for the second.

The number of participants for laptop group, tablet group and smartphone group were 21, 27 and 15.

Non-equal group sizes are expected after random assignment [29]. Tests applied in following sections were applied to the entire sample distribution. To ensure the validity of results, we randomly sampled our two larger groups so that the size was even across groups, and then performed same tests again. The result on sampled data were the same, indicating our tests were robust against the unbalanced group size.

Our study was approved by the Institutional Review Board of Rutgers University.

4.5 Password security estimation

We describe our password security estimation below.

As a measure of "uncertainty", Shannon entropy had been used in evaluating security of passwords in cryptographic contexts [10]. We used random entropy in our analysis, which was defined as in equation $H = L \times \log_2 N$, in which L was the length of the password, and N was the possible set of characters.

The NIST entropy was a scheme to evaluate human-selected passwords introduced in NIST Electronic Authentication Guideline [10]. The scheme took into account the fact that passwords were chosen by human beings, who tend to choose passwords that were easily guessed, and even from a set of a few thousand commonly chosen passwords. We implemented the scheme by assigning different entropy to characters at different positions, each password creation rule contributing a specific amount of entropy and that the entropy of the policy was the sum of the entropy contributed by each rule. In addition, we performed a simple dictionary word check ("dic-0294") to give the password extra entropy.

The adaptive password-strength meter (APSM) based on Markov models estimated the strength of a password by estimating the probability of n-grams that composed the password [11]. N-gram is a contiguous sequence of n characters from a given string. Probabilities of n-grams are computed based on a large password dataset, therefore, it introduces certain dependency on the training password dataset. In our implementation, we used the "Rockyou" password dataset to compute the database of probabilities for every n-gram. The dataset contained over 32 million real passwords. We chose 4-gram as the element in our implementation as the original paper did.

There were some other metrics we did not include in our analysis. Bonneau has proposed several statistical metrics for password security [30]. However, Bonneau's metrics were mainly applicable to a large-scale password dataset, while we had a much smaller one.

4.6 Password Cracking attacks

We performed several actual cracking attacks against our passwords. We used two popular password cracking tools, John the Ripper[1] and hashcat[2].

Dictionaries

We used various dictionaries that were common in the literature. "dic-0294" was a English dictionary from outpost9 [3]. "All" was a free public dictionary from openwall website[4]. "Mangled" was a paid dictionary from openwall. It was a hand-tuned wordlist containing four million password candidates generated using various mangle rules. "Rockyou" included about 32 million passwords leaked from the website RockYou. "Facebook" was a list of names of searchable user from the website Facebook [31]. "Myspace" contained passwords from a phishing attack against MySpace website. "Inflection"[5] was a list of words along with their different grammatical forms such as plurals and past tense.

Our dictionary set included several password databases that were compromised and disclosed to public by hackers. While they were publicly available, we were aware of the fact that they contained sensitive information. We treated them confidential, and disallowed any unauthorized access. Further, the security community in general had accepted several papers using such datasets, and thus seemed to consider it as an appropriate method.

Dictionary attack

First, we applied plain dictionary attacks using combinations of dictionaries. The first attack with "Words", which contained common words from different languages, aimed at easy passwords; the second with "Facebook", contained the entire directory from the website, aimed at passwords made with actual names, and popular phrases; the third attack with "Passwords", which contained common passwords and real leaked passwords, aimed at common and naive passwords.

Long session offline attack

We applied two long session attacks, simulating one attack with common resource and one longer attack with optimal strategies and more resources, respectively.

The first attack involved generating guesses based on a modified "Single mode" rules, which was originally from John the Ripper, using the "dic-0294" dictionary as input. The "Single mode" rules contained a set of rules to modify words including login names and directories to generate guesses [32]. The modified version, made by Weir [33], was optimized for English dictionary. We followed the same setup of Weir et al. [20].

The second attack applied the probability password crack tool developed by Weir et al. [20, 34]. It generated password guesses in the order determined by various rules derived from training sets. We used a similar model from experiment P4 conducted by Kelley et al. [35].

5 Results

We collected 189 passwords in total. Next we present our analysis results. The results focused on the analysis of password generation and password security, analysis of the passwords memorability was not included below.

[1] http://www.openwall.com/john/

[2] http://hashcat.net/hashcat/

[3] http://www.outpost9.com/files

[4] http://www.openwall.com/wordlists/

[5] http://wordlist.sourceforge.net

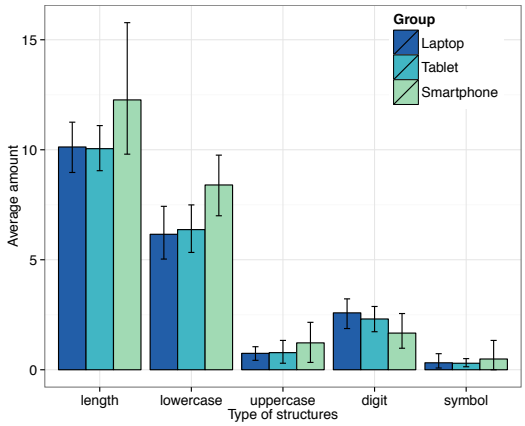

Figure 2: The average password length, amount of lowercase letters, uppercase letters, digits and symbols appeared in single password across groups. Error bars stand for 95% confidence intervals based on a bootstrap (that is, not assuming normality).

5.1 Structures

Figure 2 showed the password length and the amount of characters per password classified by types across groups. It demonstrated a notable difference in password length and amount of lowercase letters between smartphone group and other two groups.

For each structure metric, we performed one-way ANOVA test across three groups. The text entry method variable had significant effect on the amount of lowercase letters, $F(2,60) = 3.186$, $p = .048$, $\eta_p^2 = .066$. No significant result was found from other metrics.

Next, we examined the categories of passwords each group generated. We defined the category of a password by types of characters it contained. The category of a password revealed the complexity in its structures: passwords containing multiple types of characters had a more complex structure than ones with only one type. Table 1 summarized our definition of categories.

Figure 3 showed the distribution of passwords within the defined categories across groups. For smartphone group, passwords that contained only lowercase letters (*loweralpha*) was most common (31.1%). For other two groups, passwords containing only lowercase letters and digits (*loweralpha-num*) were the most common: 30.2% in laptop group and 38.2% in tablet group, respectively. In addition, there was no passwords containing lowercase letters, special symbols and digits (*loweralpha-special-num*) in smartphone group at all, while both other groups generated passwords in that category.

Category	Description
loweralpha-num	only contains lowercase letters and digits
loweralpha	only contains lowercase letters
mixedalpha-num	contains lowercase and uppercase letters and digits
loweralpha-special-num	contains lowercase letters, special symbols and digits
all	contains lowercase and uppercase letters, special symbols and digits
mixedalpha	only contains lowercase and uppercase letters
others	types other than mentioned ones

Table 1: Definition of each category of passwords. All types with low occurrence in our passwords were aggregated into "others" category.

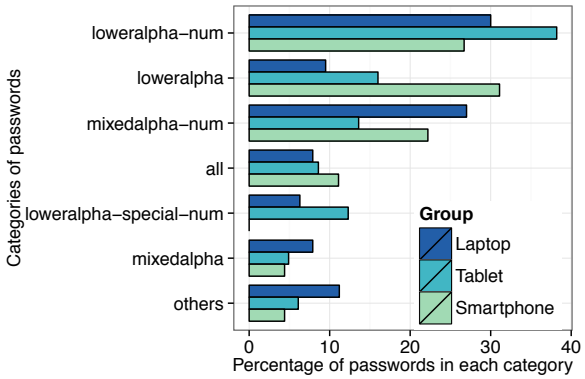

Figure 3: A comparison of distribution of passwords in different categories for each group.

5.2 Quantitative password security

We estimated the security of our passwords with two common entropy-based password security metrics, random entropy and NIST entropy, and a more recent Markov model based metric (APSM). Such metrics provided quantitative measurement of password security. Three metrics were explained in details in section 4.3. The mean scores and corresponding confidence intervals of the result were shown in Figure 4. According to the graph, scores of passwords of smartphone group were consistently higher than that of other two groups. However, most of means stayed within the confidence interval of the value of other groups, indicating the differences among groups were limited.

We performed one-way ANOVA on the three sets of security measures. However, the results showed non-significant effect of text entry method variable on them.

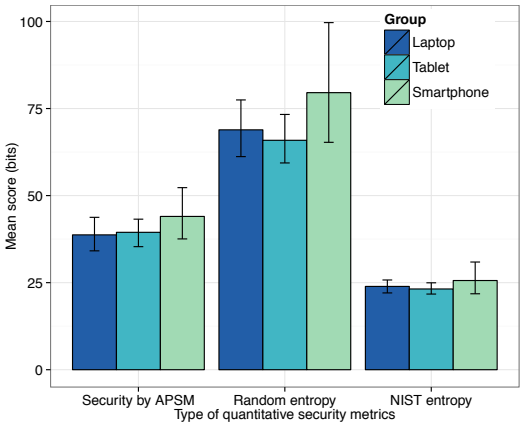

Figure 4: The mean score of three password security metrics across groups: score from Adaptive Password-Strength Meter (APSM), random entropy and NIST entropy. Error bars stand for 95% confidence intervals based on a bootstrap (that is, not assuming normality).

5.3 Cracking attacks

We performed dictionary attacks and long-session offline attacks on our collected passwords. Both attacks have been described in details in section 4.4. Table 2 showed the result of plain dictionary attacks. The performance of "Words" and "Facebook" attacks were limited across all groups, except "Facebook" attack on passwords in smartphone group. The "Password" attack worked much better compared to the first two attacks against laptop and tablet group, while it had very limited improvement over previous attacks against smartphone group.

The results of two long session offline attacks were shown in Figure 5 and Figure 6, respectively. According to the figures, although the lowerbounds of resistance (the number of guesses of the first cracked password) were different, the percentages of cracked passwords across groups were similar to each other.

When we combined cracked passwords from all attacks together, the total number of cracked passwords for laptop group, tablet group and smartphone group were 24 (38.1%), 24 (29.6%) and 16 (35.6%), respectively. Chi-square test had been performed on the cracked password ratio across groups, but no significant result was found ($\chi^2(2) = 1.21, p = 0.54$).

Figure 7 showed the distribution of all cracked passwords into different categories across groups, in which we saw quite different distributions. Particularly, the category with the largest percentage of cracked passwords was different for all three groups: *mixedalpha-num* (passwords contain uppercase letters, lowercase letters and digits) (10, 15.9%), *loweralpha-num* (13, 16.0%) and *loweralpha* (7, 15.6%), respectively.

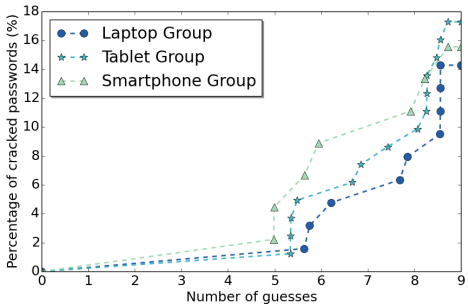

Figure 5: The percentage of passwords cracked by our first offline attack. The x-axis was in log scale. The final percentage of cracked passwords for laptop group, tablet group and smartphone group were 14.2%, 17.3% and 15.6%, respectively.

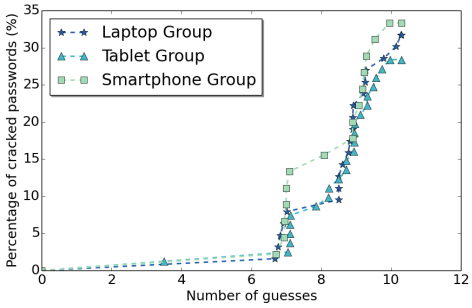

Figure 6: The percentage of passwords cracked by Weir's algorithm vs. the number of guess, per group. The x-axis was in log scale. The final percentage of cracked passwords for laptop group, tablet group and smartphone group are 31.7%, 28.4% and 30%, respectively.

5.4 Task load

We used TLX forms to evaluate the subjective task load of our study. These questions revealed participants' subjective assessment towards tasks in the study. Figure 8 showed the mean scores for each question of TLX form for both sessions.

Given individual items in one TLX form were correlated, we applied MANOVA test with the text entry method as variable on the six items together, for session one and two, respectively. The result showed a non-significant effect of text entry method type on the scores of TLX assessment both for session one, $V = 0.21, F(8,116) = 1.70, p = 0.11$, and session two, $V = 0.28, F(12,100) = 1.37, p = 0.19$. Therefore, we concluded that participants in groups did not feel significantly different about the subjective task load of the experiment they participated in.

Name	Include	Size	Laptop group (63)	Tablet group (81)	Smartphone group (45)
Words	“dic-0294”, “all”, “inflection”	4.1M	4 (6.3%)	4 (4.9%)	4 (8.9%)
Facebook	“facebook”	37.3M	3 (4.8%)	6 (7.4%)	7 (15.6%)
Passwords	“mangled”, “rockyou”	54.8M	15 (23.8%)	12 (14.8%)	8 (17.8%)
Long-session 1	NA	1000M	9(14.2%)	14(17.3%)	7(15.6%)
Long-session 2	NA	20000M	20(31.7%)	23(28.4%)	13(30%)

Table 2: Results of both plain dictionary attacks and long-session offline attacks. “Include” listed all dictionaries we used in each attack. The size was the number of unique entries each combined dictionary had for dictionary attacks, and the number of guesses generated per password for long-session offline attacks.

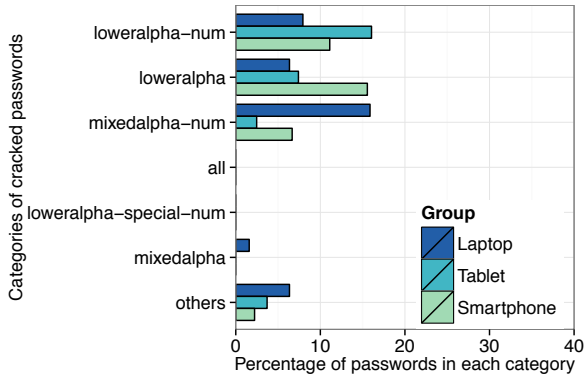

Figure 7: A comparison of percentages of cracked passwords in different categories across groups. The percentage value showed the percentage of cracked password in total amount of passwords in each group. We kept the categories and percentage scale as the same as in Figure 3 for better comparison. Cracked passwords here were the combination of cracked passwords in all our attacks.

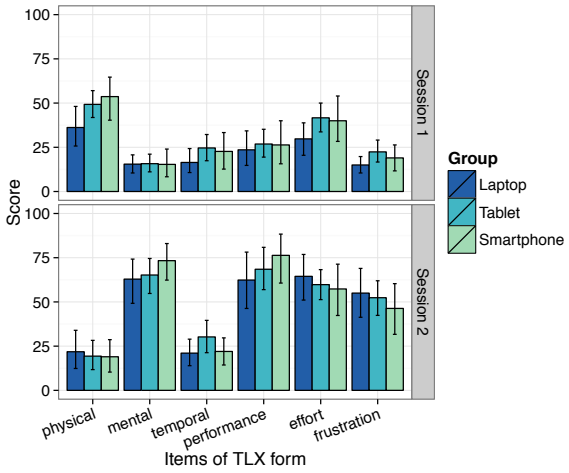

Figure 8: Mean score for each item in TLX form in session one and two. Error bars stand for 95% confidence intervals based on a bootstrap (that is, not assuming normality).

6 Discussion and Conclusions

Our experiment successfully identified significant effect in password structures. In particular, passwords generated by smartphone group consisted much more lowercase letters per password than other groups. However, quantitative security estimations, including random entropy, NIST entropy and score of APSM, did not differ significantly for passwords from different groups.

One possible reason of such result could be that while passwords consisted more lowercase letters were considered weaker, smartphone group actually generated longest passwords in average (around 12.5, compared to 10 in other groups, see Figure 2). Extra length made passwords more secure. For example, a 15-character-long lowercase-only password from smartphone group scored 101, 28.5 and 48 in random entropy, NIST entropy and APSM, respectively. All of them are well above overall average.

In our study, smartphone keyboard demanded most effort in switching layouts. As a result, participants switched layouts less often in smartphone group, leading to more lowercase letters in passwords. However, participants still paid sufficient effort on passwords, resulting in long passwords. According to Shay et al. [21], long passwords were generally more secure. Meanwhile, smartphone group participants did not report a higher load in TLX forms (Figure 8).

This is not to deny the fact that the difficulty in reaching non-lowercase letters affected password security for smartphone group. For two 10-character passwords from our study, the one with lowercase, uppercase and digits scored much higher than the one with only lowercase letters in our security estimation.

Therefore, one simple design modification for text entry methods in smartphone group could be including digits or some special symbols in the first layout of the keyboard, without sacrificing usability. Such design could encourage people to choose non-lowercase characters more often.

Also, the study is conducted as a lab study, in which participants created passwords under the watch of exper-

imenters. It is possible that under such condition, participants spent extra effort to create passwords that are stronger than usual. For example, the average password length of each group in our study is at least 10, while that of RockYou passwords is below 8.

In addition, whether the quantitative metrics we used reflected the true security of passwords was still a question. Random entropy and NIST entropy had been criticized in such task [20, 30], which led us to include one more recent metic (APSM). We found that APSM could also compute quite different scores for very similar passwords. For example, "vowelword" and "bonesjones" were both lowercase-only letters consisted of two English words; however, APSM computed their scores to be 50 bits and 30 bits, respectively. This could be because APSM is dictionary dependent. Considering the mean score of APSM of our passwords were only 40 bits, a difference of 20 bits would be undismissible. Therefore, our study raised the need of a truly comprehensive and appropriate metric for gauging text password security.

On the other hand, the analysis of password structure and cracking attacks still showed the effect existed. As mentioned before, the variable had significant effect on number of lowercase letters in passwords (Figure 2). This finding was consistent with our experiment design, as the difficulty of reaching non-lowercase keys in the smartphone group was increased. In addition, we found that passwords cracked in our attacks distributed quite differently in categories across groups (Figure 7). Particularly, nearly 50% of cracked passwords in every group belonged to a different single category compared with each other. It showed different resistance against cracking attacks across groups.

Limitations. Our sample size was relatively small, a large-scale study would be desired in the future. In addition, our study limited participants to create and recall passwords in a lab environment, which is not close to the real scenario when passwords are used. While recent study by Fahl et al. [24] showed that laboratory studies generally create useful data, a field study could be a follow-up on this topic. Also, while in our study we used common text entry methods, one could include more manipulations to see how would the effect be changed due to specific manipulations.

Conclusions. We presented the analysis of passwords created with different text entry methods. We designed and executed an experiment that aimed at exploring the possible effect of text entry methods on password security. Our results showed that the effect was not as significant as we hypothesized. The structure of passwords had been affected by such variable. However, it did not have significant effect on password security, according to our quantitative security estimation and cracking attacks. More work is needed to pinpoint the magnitude of the effect and exact design factors in text entry methods that affecting people's password generation process.

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