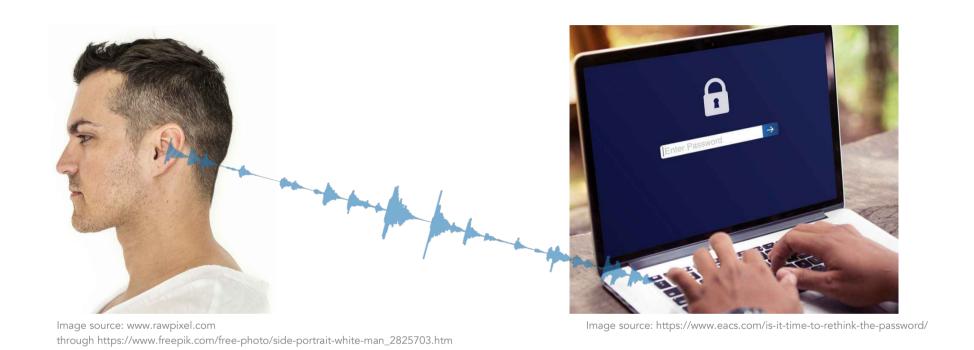
#### White Hat: Hacking Passwords Using ML



Image source: https://www.bearfoxmarketing.com/white-hat-link-building/

tikka (Tikeswar Naik) 28 Oct 2019 tikeswar@gmail.com

#### Problem Statement



Can we figure out what someone is typing, just by *listening to the keystrokes*?

#### Motivations

- Security implications
  - Typing passwords while people are around, or during teleconferencing
  - Can someone hack your computer microphone and listen to what you type?

kido [= Keystroke Decode]
- a ML project to explore this idea



Image source: https://www.masterfile.com/image/en/621-00746221/executives-teleconferencing



Image source: https://www.quora.com/Where-is-the-built-in-microphone-located-on-a-MagBook-Pro

#### Outline

- Data Gathering, and Preparation
- Training and Eval
- Testing and Error Analysis
  - Reality check ...
  - How to improve model accuracy?
- Final Remarks; Links

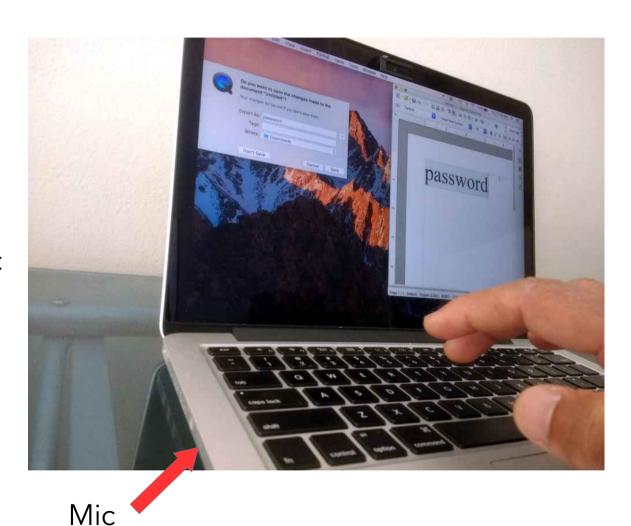
## Data Gathering

#### Used my MacBook Pro:

- Keyboard to type
- QuickTime Player to record audio of typing through the inbuilt mic

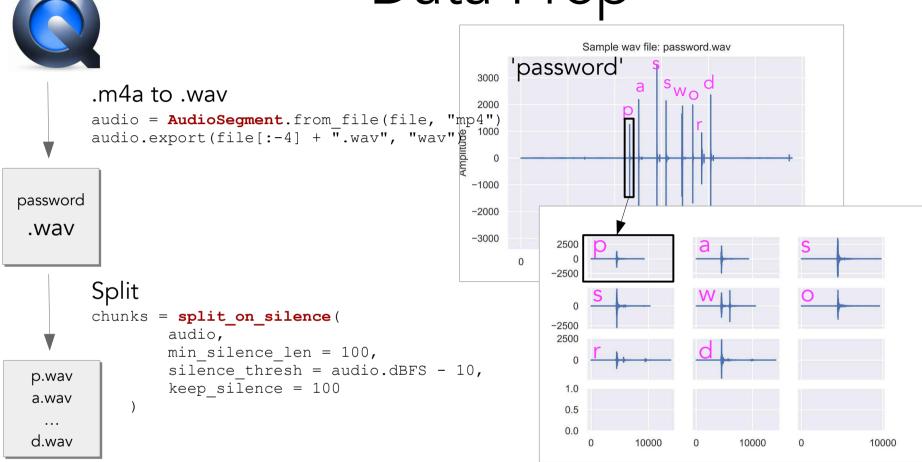
#### Advantages:

- Data has less variability
- And thus it helps us focus on proving (or disproving) the concept without much distraction





## Data Prep

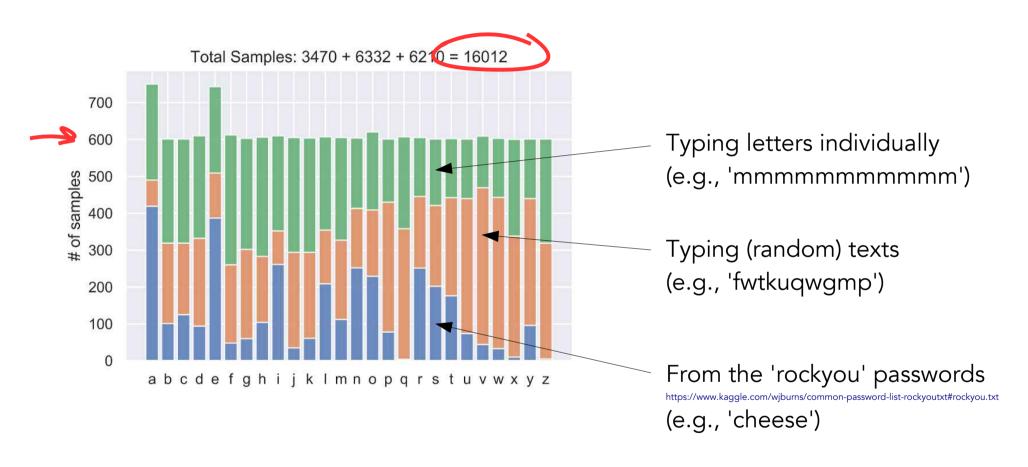




## Data Prep

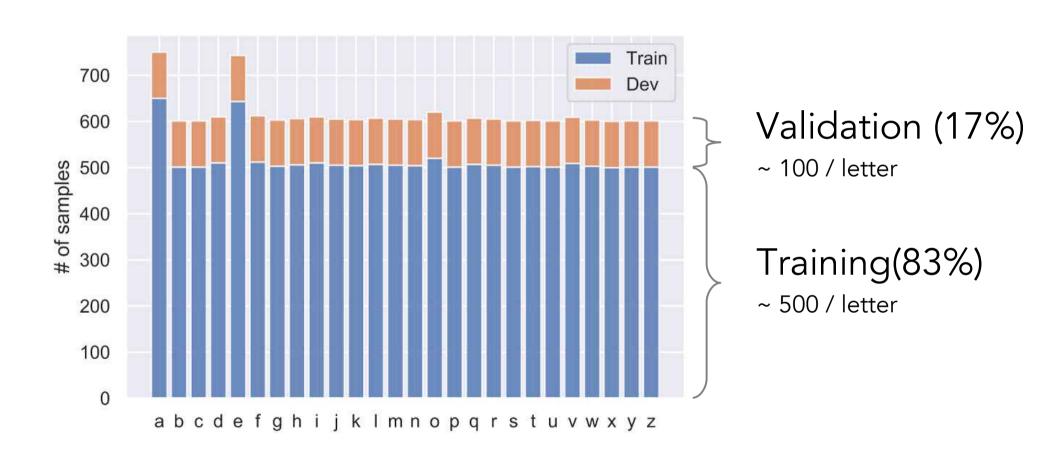
```
Sample way file: password.way
                                                        password
        .m4a to .wav
                                                    2000
        audio = AudioSegment.from file(file, "mp4")
        audio.export(file[:-4] + ".wav", "wav"
                                                   -1000
password
                                                   -2000
 .wav
                                                   -3000
        Split
        chunks = split on silence(
                                                            -2500
                 audio,
                                                             2500
                 min silence len = 100,
                 silence thresh = audio.dBFS - 10,
 p.wav
                 keep silence = 100
                                                                                      password_chunk0_p
                                                              1.0
 a.wav
                                                              0.5
                                                              0.0
 d.wav
        Spectrogram
        rate, data = wavfile.read(wav file)
        data1D = data[:, 0]
        fig, ax = plt.subplots(1)
        s2d, f1d, t1d, im = ax.specgram(x=data1D, Fs=rate, noverlap=384, NFFT=512)
p, a, ..., d
 .png
```

# Data Samples

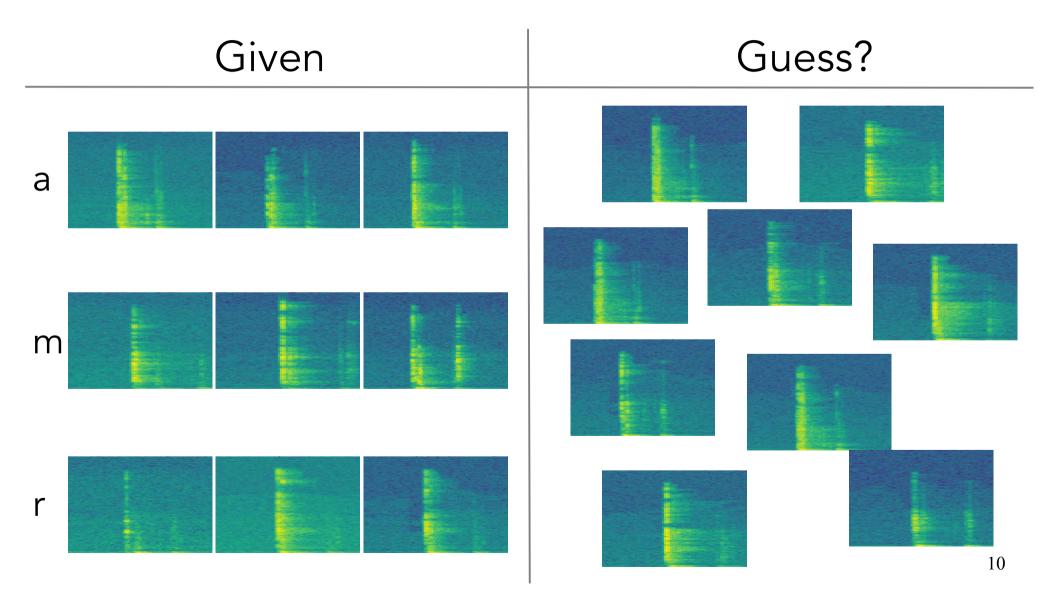


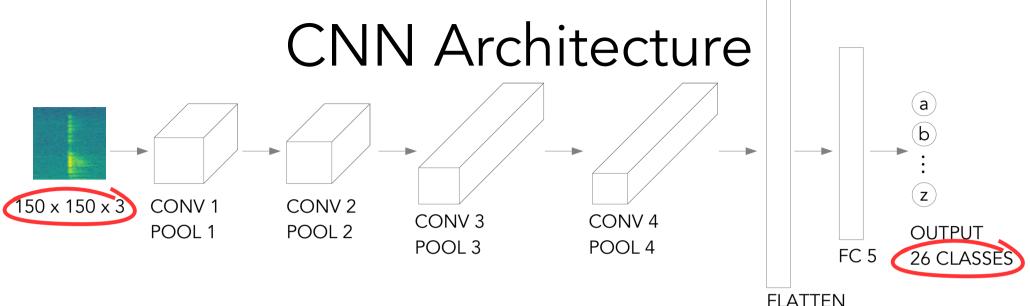
Total # of samples: ~ 16,000 # of samples / letter: ~ 600

# Train-Validation Split



#### The ML Problem in a Nutshell ...



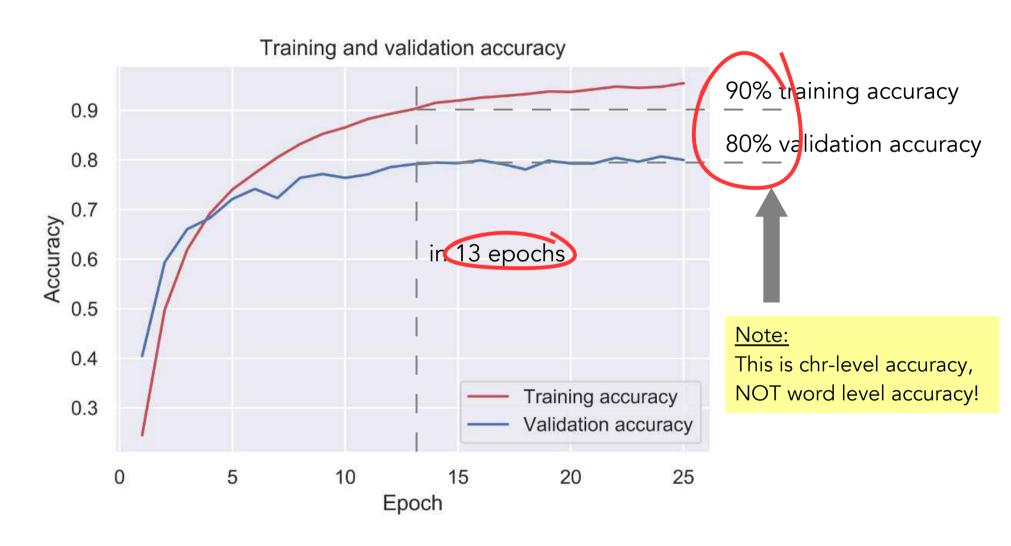


```
model = tf.keras.models.Sequential([
    # 1st convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu', input shape=(150, 150, 3)),
    tf.keras.layers.MaxPooling2D(2, 2),
    # 2nd convolution
    tf.keras.layers.Conv2D(64, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # 3rd convolution
    tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # 4th convolution
    tf.keras.layers.Conv2D(128, (3,3), activation='relu'),
    tf.keras.layers.MaxPooling2D(2,2),
    # Flatten the results to feed into a DNN
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dropout(0.5),
    # FC laver
    tf.keras.layers.Dense(512, activation='relu'),
    # Output layer
    tf.keras.layers.Dense(26, activation='softmax')
```

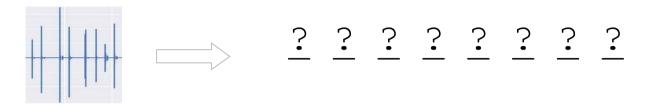
#### FLATTEN DROPOUT

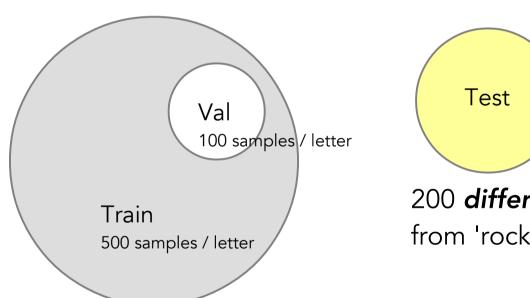
Layer (type)	Output	Shape	Param #
======================================	(None,	148, 148, 64)	1792
max_pooling2d_4 (MaxPooling2	(None,	74, 74, 64)	0
conv2d_5 (Conv2D)	(None,	72, 72, 64)	36928
max_pooling2d_5 (MaxPooling2	(None,	36, 36, 64)	0
conv2d_6 (Conv2D)	(None,	34, 34, 128)	73856
max_pooling2d_6 (MaxPooling2	(None,	17, 17, 128)	0
conv2d_7 (Conv2D)	(None,	15, 15, 128)	147584
max_pooling2d_7 (MaxPooling2	(None,	7, 7, 128)	0
flatten_1 (Flatten)	(None,	6272)	0
dropout_1 (Dropout)	(None,	6272)	0
dense_2 (Dense)	(None,	512)	3211776
dense_3 (Dense)	(None,	26)	13338
			11

# **CNN** Training

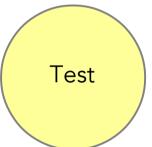


## Testing





Total # of samples: ~ 16,000



200 different [pass]words from 'rockyou'

#### Testing (contd.) 200 test words CONV 1 CONV 2 CONV 3 CONV 4 POOL 1 POOL 2 POOL 3 POOL 4 FLATTEN DROPOUT W

# Testing (contd.)

#### Test Examples

#### <u>Actual</u>

aaron

canada

lokita

#### **Predicted**

s s i o b

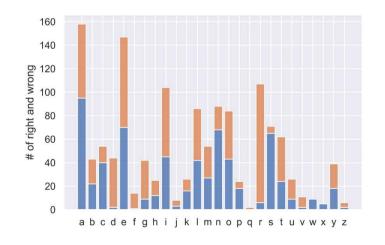
canzwa

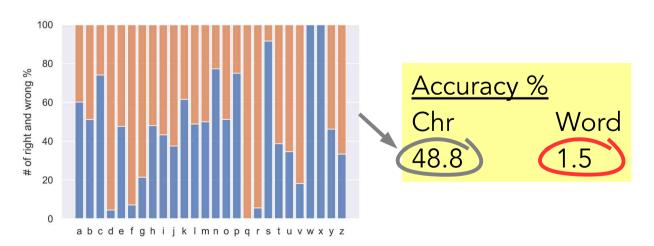
lokita

#### **Correct Ones**

c a n a

lokita



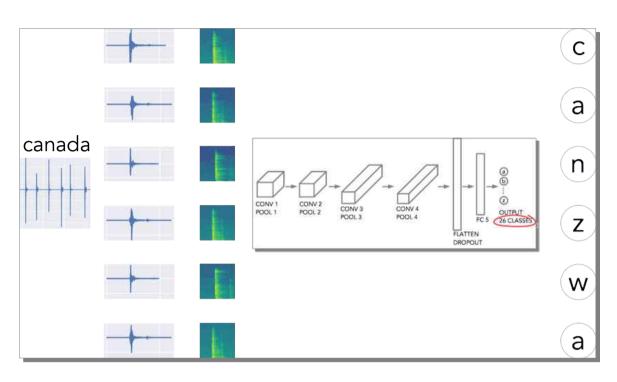


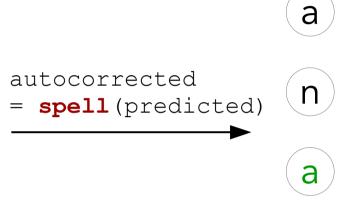
## Error Analysis

# Test ExamplesActual<br/>a a r o nPredicted<br/>s s i o bCorrect Ones<br/>--- o -c a n a d ac a n z w ac a n \_ \_ al o k i t al o k i t al o k i t a

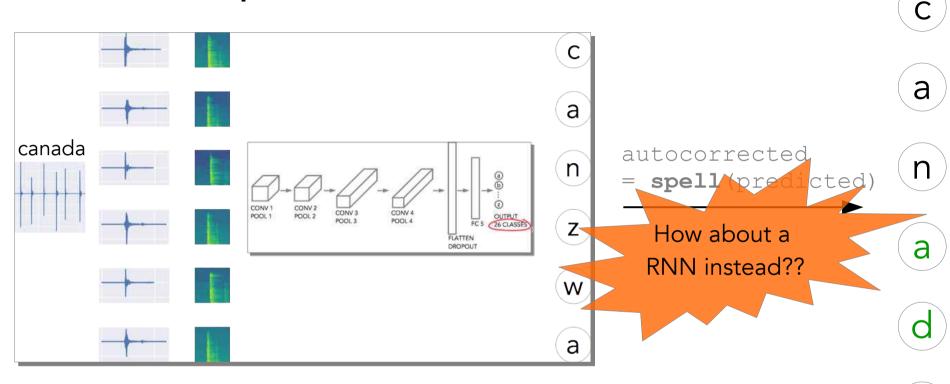
What if we pass it through a spellchecker?!

# Improving Model Accuracy





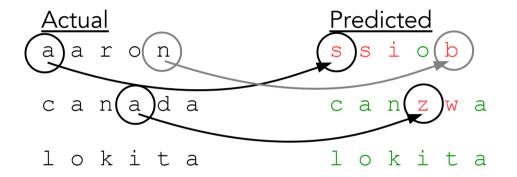
# Improving Model Accuracy



	<u>Chr</u>	Word
CNN Predicted accuracy:		1.5
+ Autocorrected accuracy:	49.5	8.0
		7~~

## More Error Analysis

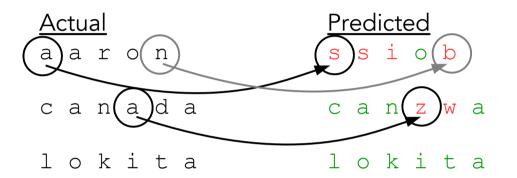
#### Test Examples



#### **Correct Ones**

## More Error Analysis

#### Test Examples



#### **Correct Ones**

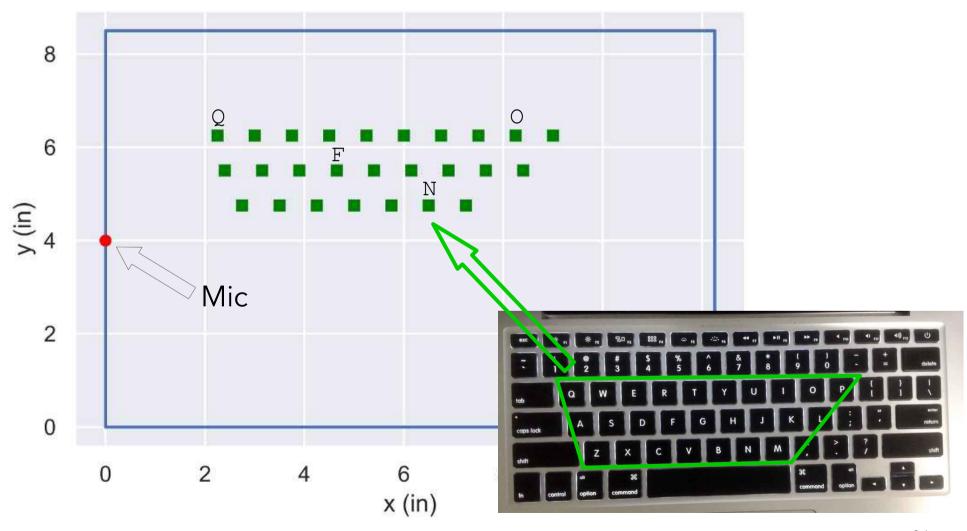
\_ \_ \_ \_ \_ \_ \_ \_

c a n a

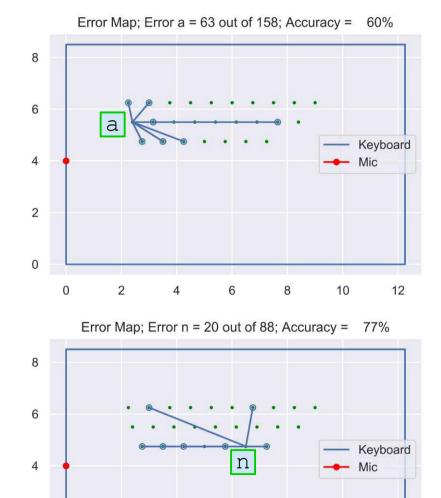
lokita

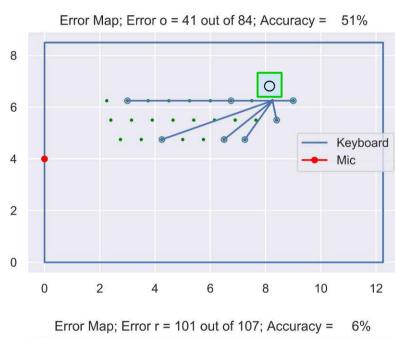


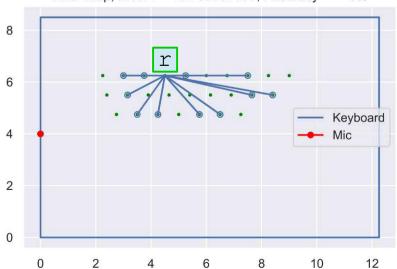
# More Error Analysis



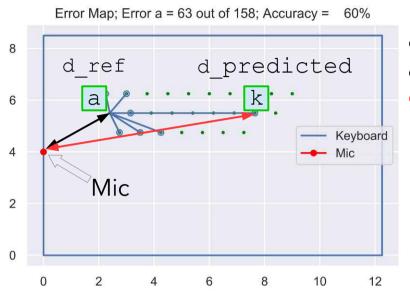
# Error Map (Samples)





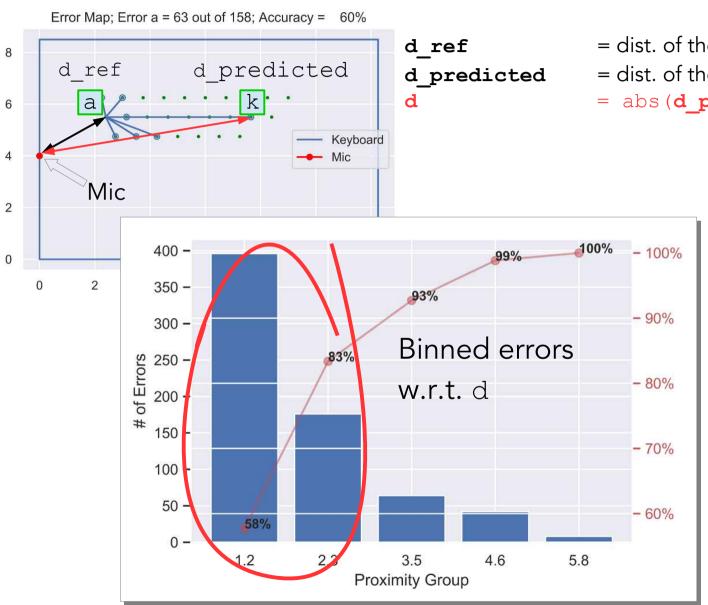


## Error Groups



Bin the errors w.r.t. d

## Error Groups



- = dist. of the reference letter from the mic
- = dist. of the predicted letter from the mic
- = abs(d\_predicted d\_ref)

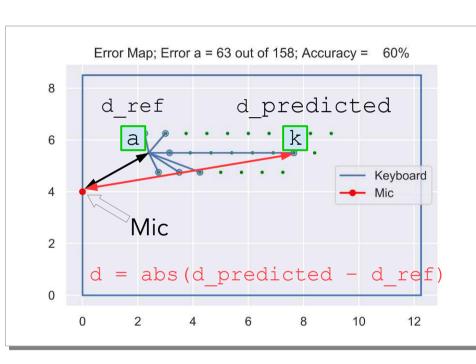
Most errors are from the close proximity

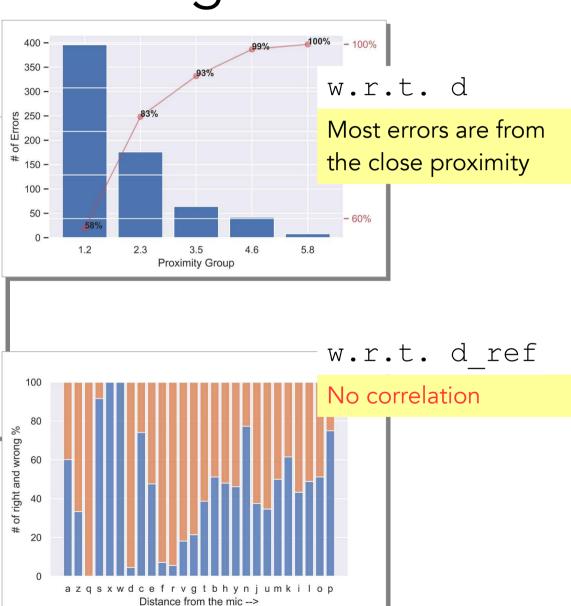
=>

=>

- More data
- Bigger network
- Network
   architecture that can
   capture this better

# One more thing ...





#### Summary

- It seems possible to hack the keystroke sounds
- With a fairly small amount of data and a simple CNN architecture + spell check, we can get a non-trivial word-level accuracy

	<u>Chr</u>	Word
CNN Predicted accuracy:		1.51
+ Autocorrected accuracy:	49.5	8.0

#### Model Enhancements ?

## Thoughts

- Normal typing speed 
   challenging signal processing (to isolate individual keystrokes)
  - Here I had typed slow one letter at a time
- Any keystrokes 
   Challenging signal processing (Caps Lock on?, Shift?, ...)
  - Here I had used only lower-case letters (no upper case letters, digits, special characters, special keystrokes, etc. were included)
- Background noise 2 add noise
  - Here during the data recording some simple and light background noise of a car passing by were present in some cases, but no complex background noise (cafeteria background noise for example)
- Different keyboards and microphone settings + different persons typing 2 more data + data augmentation + bigger network + different network architecture
- Can we use vibration signature instead of audio signature?

#### Thank You!

```
Code, data, resources:
https://github.com/tikeswar/kido
Contact:
tikka / tikeswar@gmail.com
```