

White Hat: Hacking Passwords Using ML

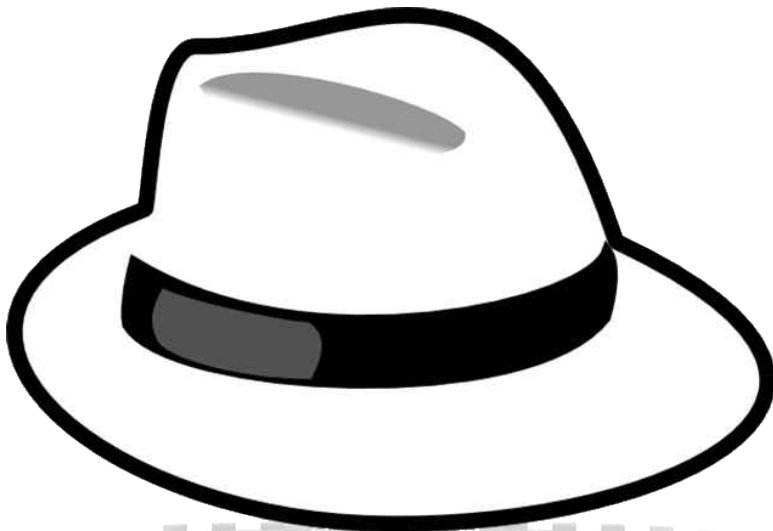


Image source: <https://www.bearfoxmarketing.com/white-hat-link-building/>

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Problem Statement



Image source: www.rawpixel.com
through https://www.freepik.com/free-photo/side-portrait-white-man_2825703.htm



Image source: <https://www.eacs.com/is-it-time-to-rethink-the-password/>

Is it possible to 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>

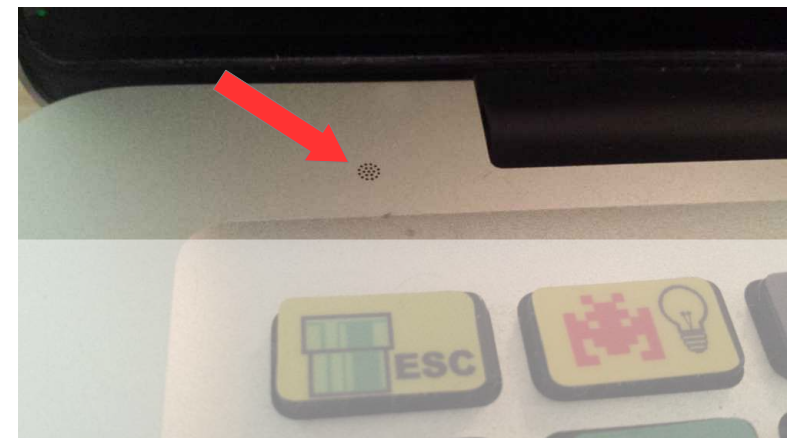


Image source:
<https://www.quora.com/Where-is-the-built-in-microphone-located-on-a-MacBook-Pro>

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



Mic

Data Prep



.m4a to .wav

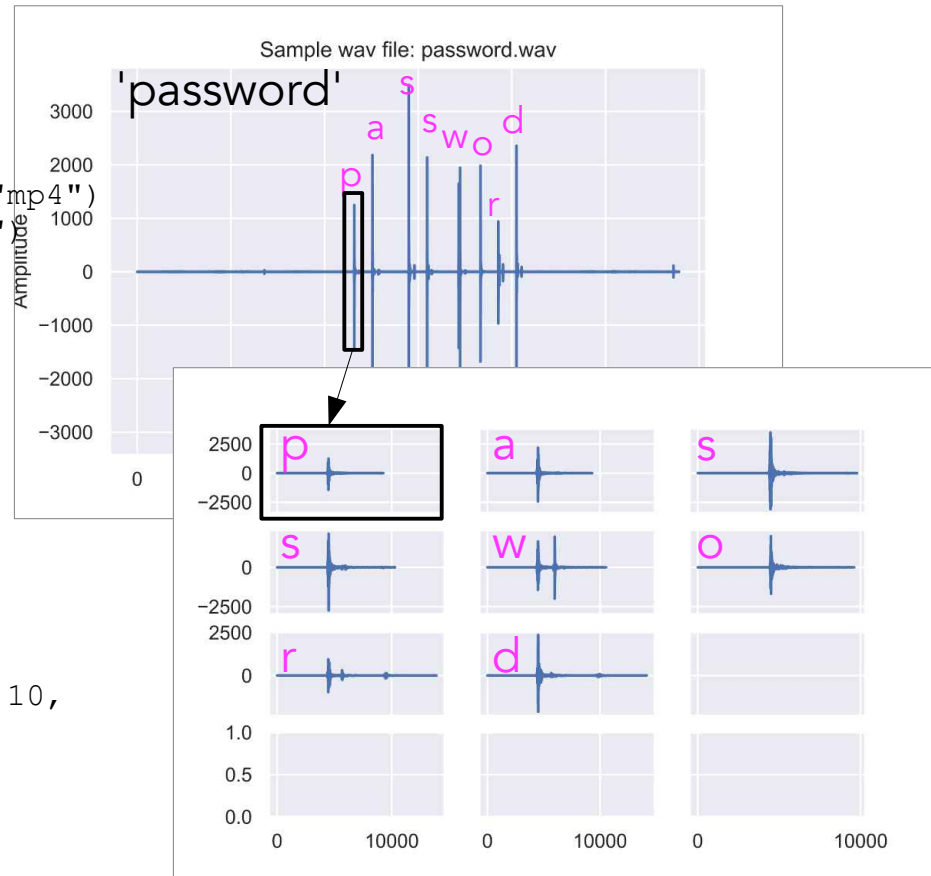
```
audio = AudioSegment.from_file(file, "mp4")  
audio.export(file[:-4] + ".wav", "wav")
```

password
.wav

Split

```
chunks = split_on_silence(  
    audio,  
    min_silence_len = 100,  
    silence_thresh = audio.dBFS - 10,  
    keep_silence = 100  
)
```

p.wav
a.wav
...
d.wav





Data Prep

.m4a to .wav

```
audio = AudioSegment.from_file(file, "mp4")
audio.export(file[:-4] + ".wav", "wav")
```

password
.wav

Split

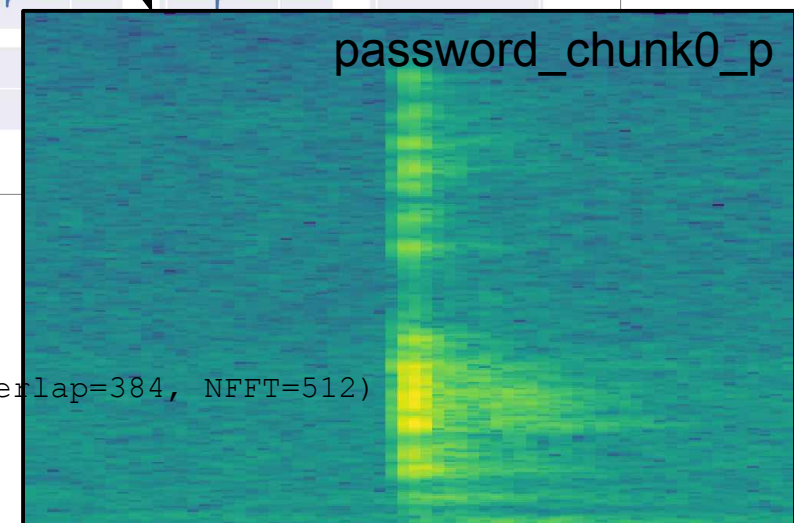
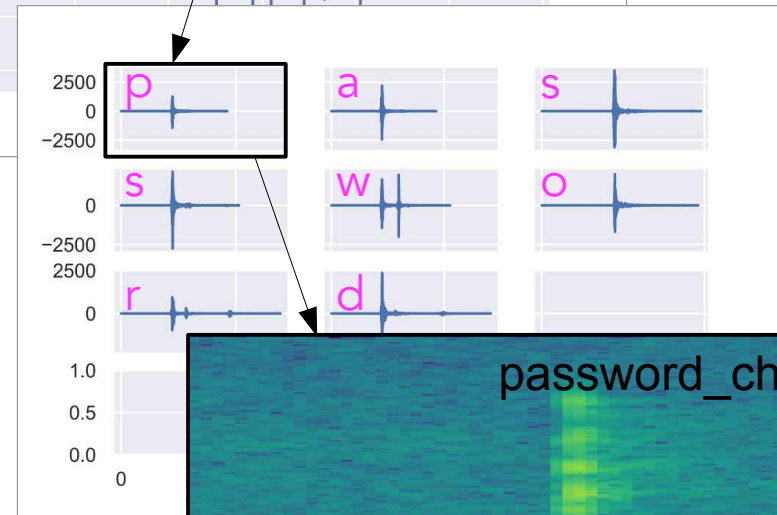
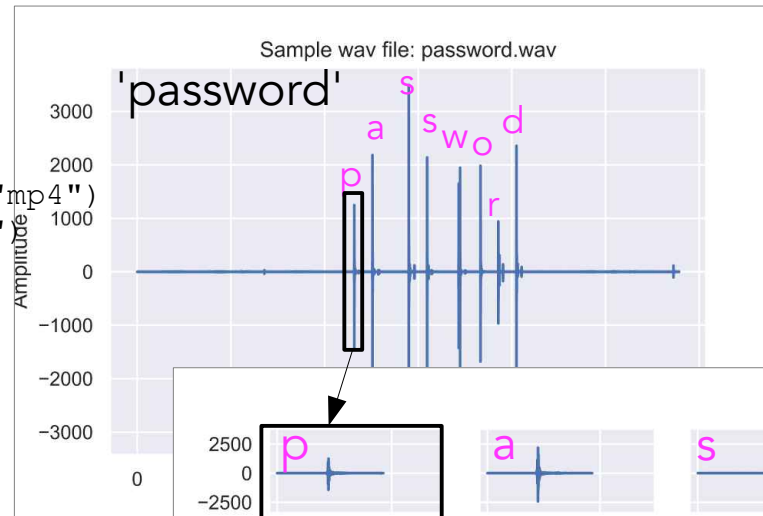
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p.wav
a.wav
...
d.wav

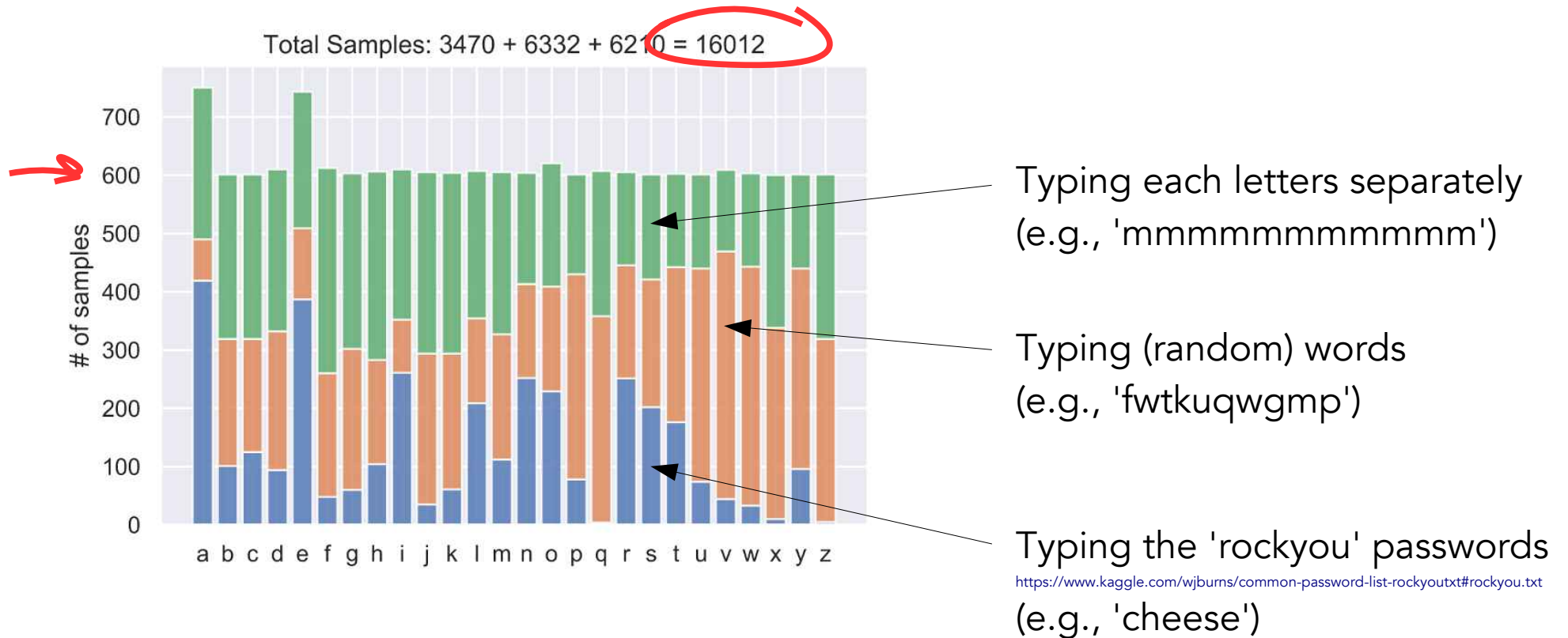
Spectrogram

```
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

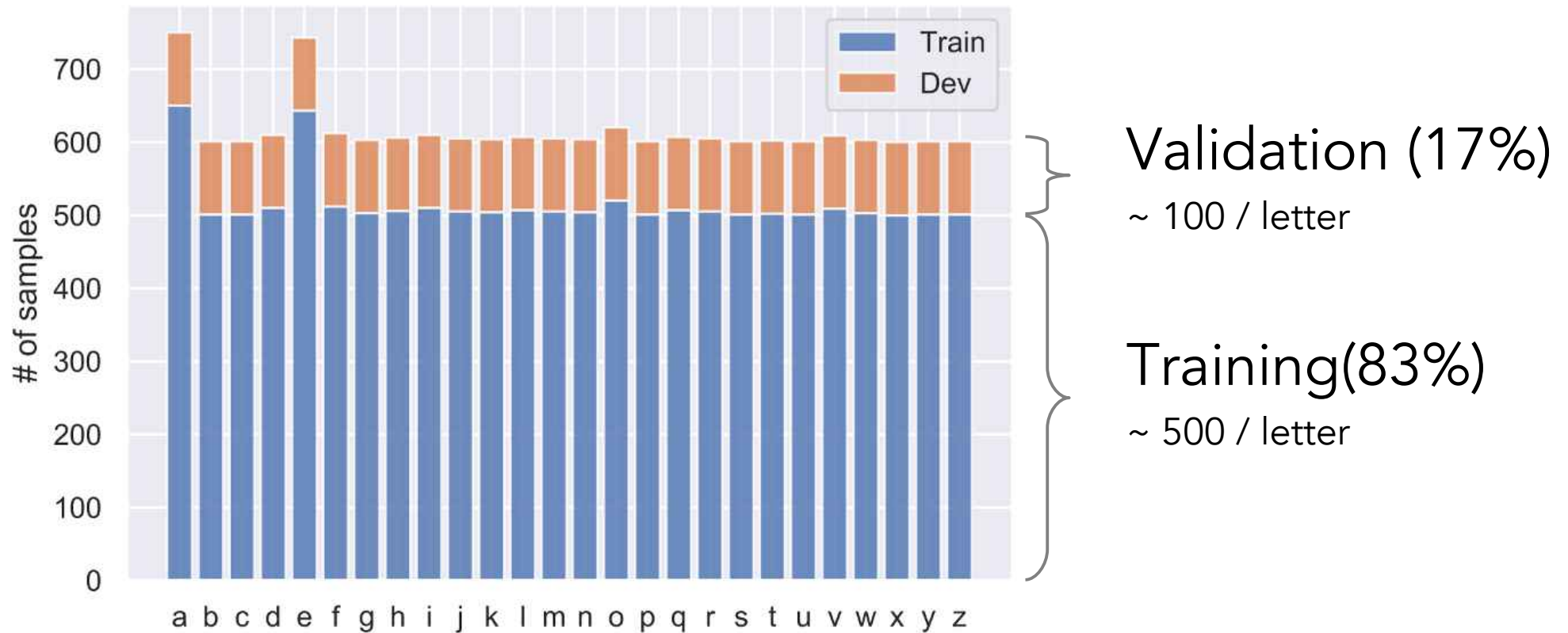


Data Samples



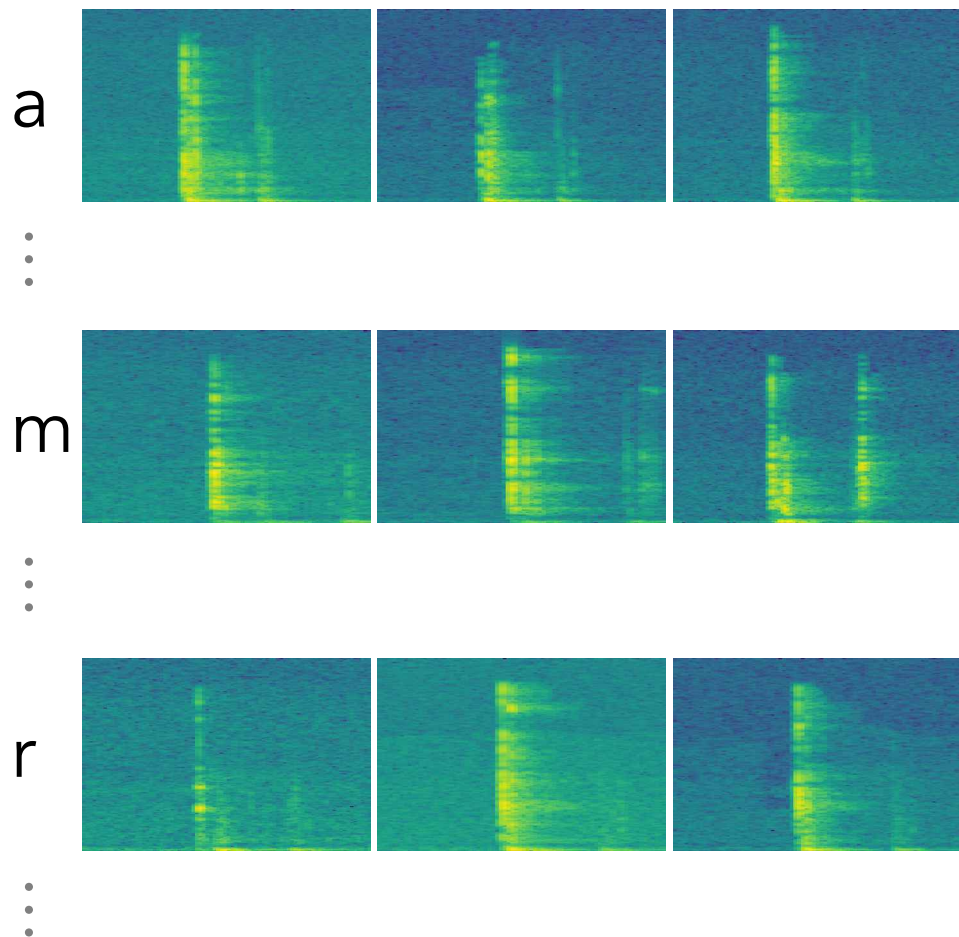
Total # of samples: ~ **16,000**
of samples / letter: ~ **600**

Train-Validation Split

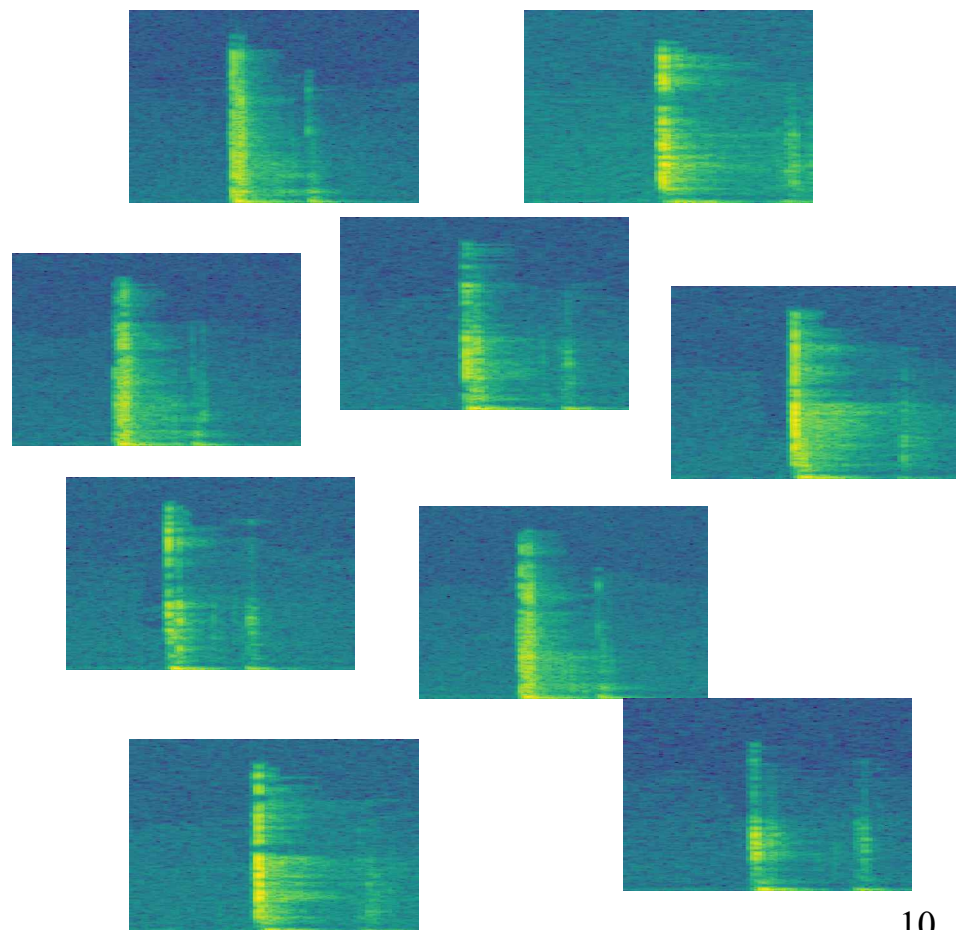


The ML Problem in a Nutshell ...

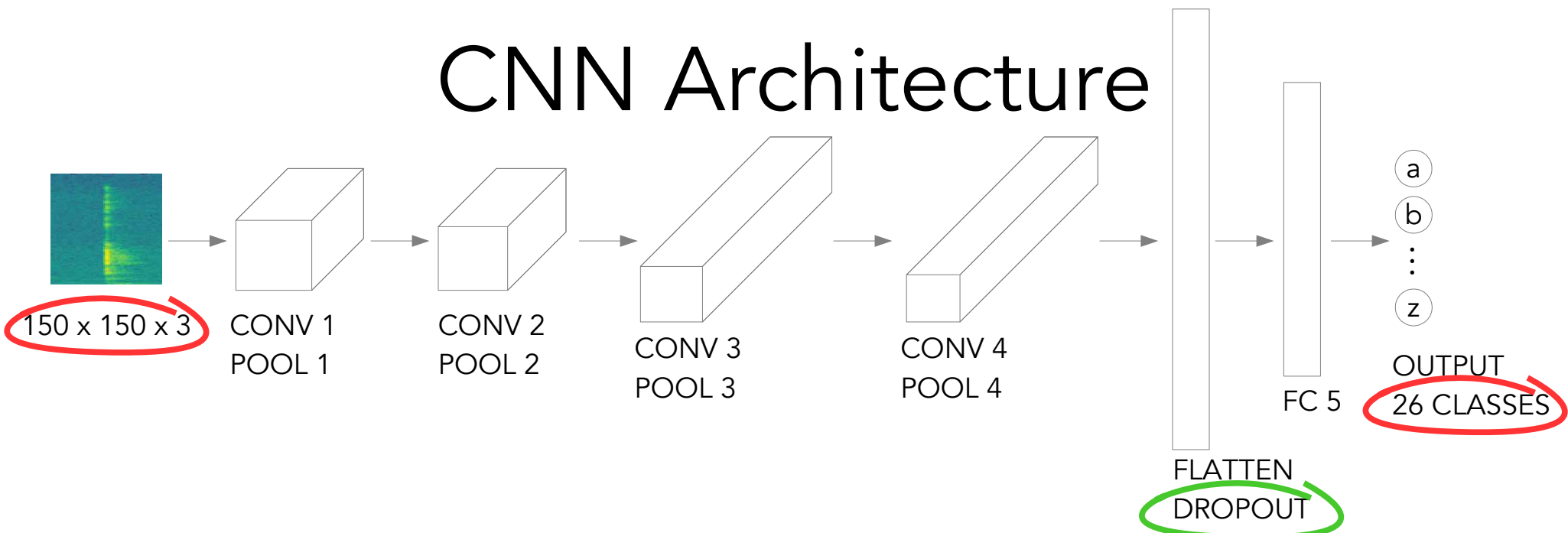
Given



Guess?



CNN Architecture



```
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),

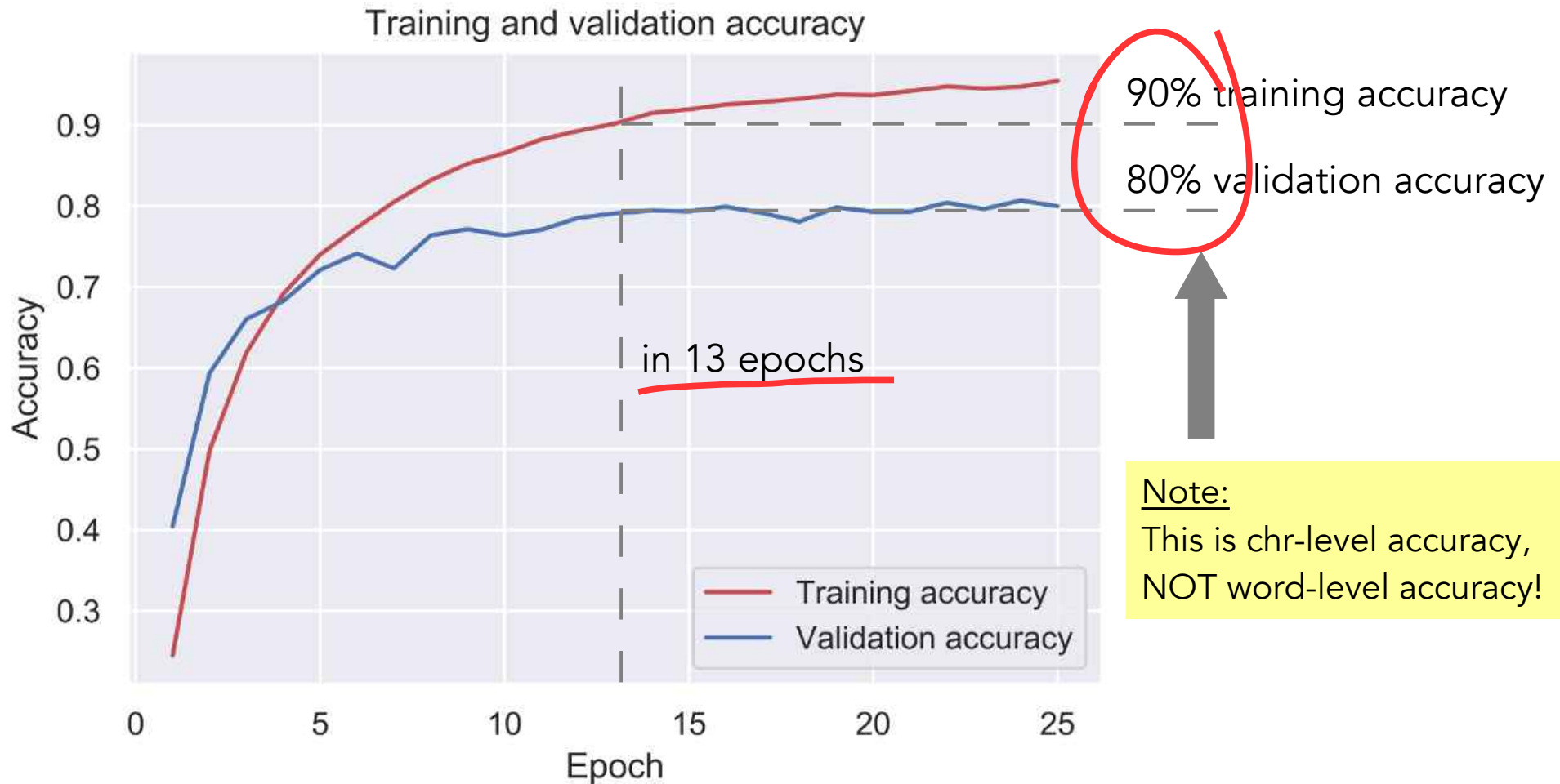
    # Flatten the results to feed into a DNN
    tf.keras.layers.Flatten(),
    tf.keras.layers.Dropout(0.5),

    # FC layer
    tf.keras.layers.Dense(512, activation='relu'),

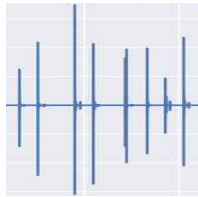
    # Output layer
    tf.keras.layers.Dense(26, activation='softmax')
])
```

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(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
Total params: 3,485,274		
Trainable params: 3,485,274		
Non-trainable params: 0		

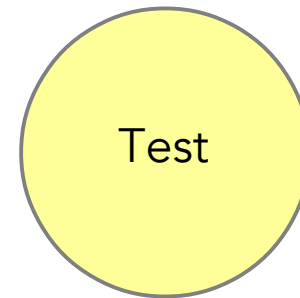
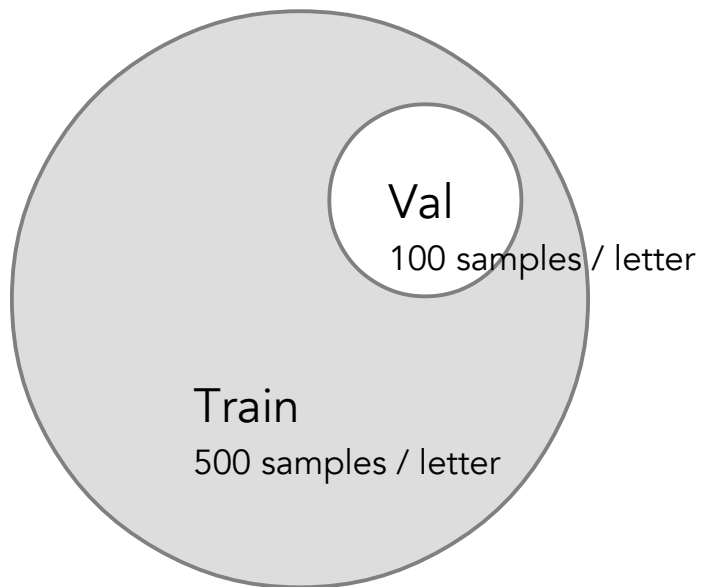
CNN Training



Testing



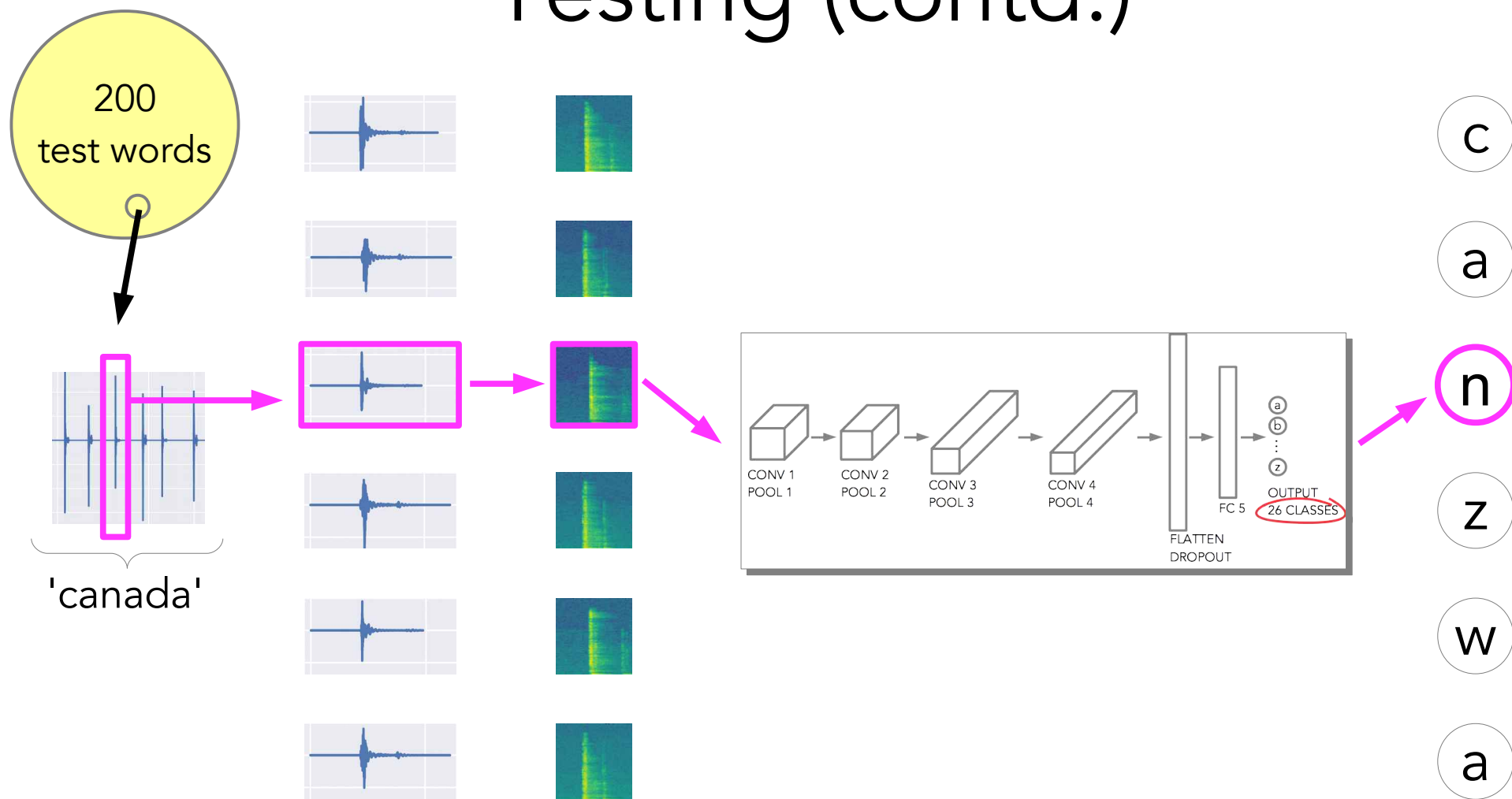
? ? ? ? ? ? ? ?



200 **different** [pass]words
from 'rockyou'

Total # of samples: ~ **16,000**

Testing (contd.)



Testing (contd.)

Test Examples

Actual

a a r o n

c a n a d a

l o k i t a

Predicted

s s i o b

c a n z w a

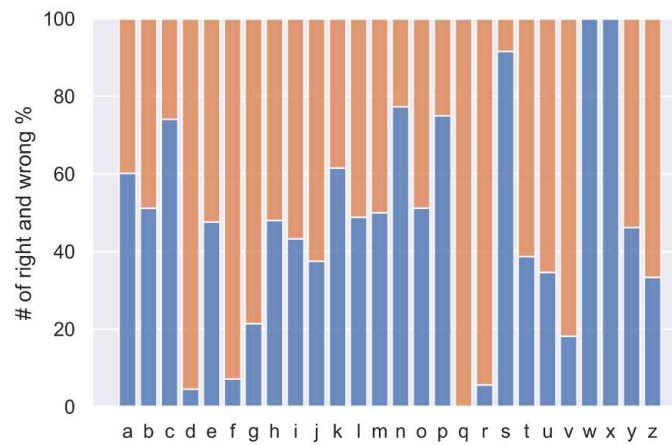
l o k i t a

Correct Ones

_ _ _ o _

c a n _ _ a

l o k i t a



Accuracy %

Chr

48.8

Word

1.5

Error Analysis

Test Examples

Actual

a a r o n

Predicted

s s i o b

Correct Ones

_ _ _ o _

c a n a d a

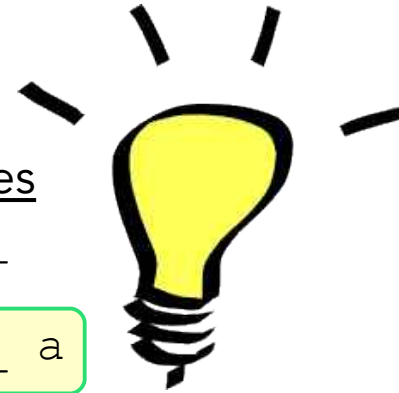
c a n z w a

c a n _ _ a

l o k i t a

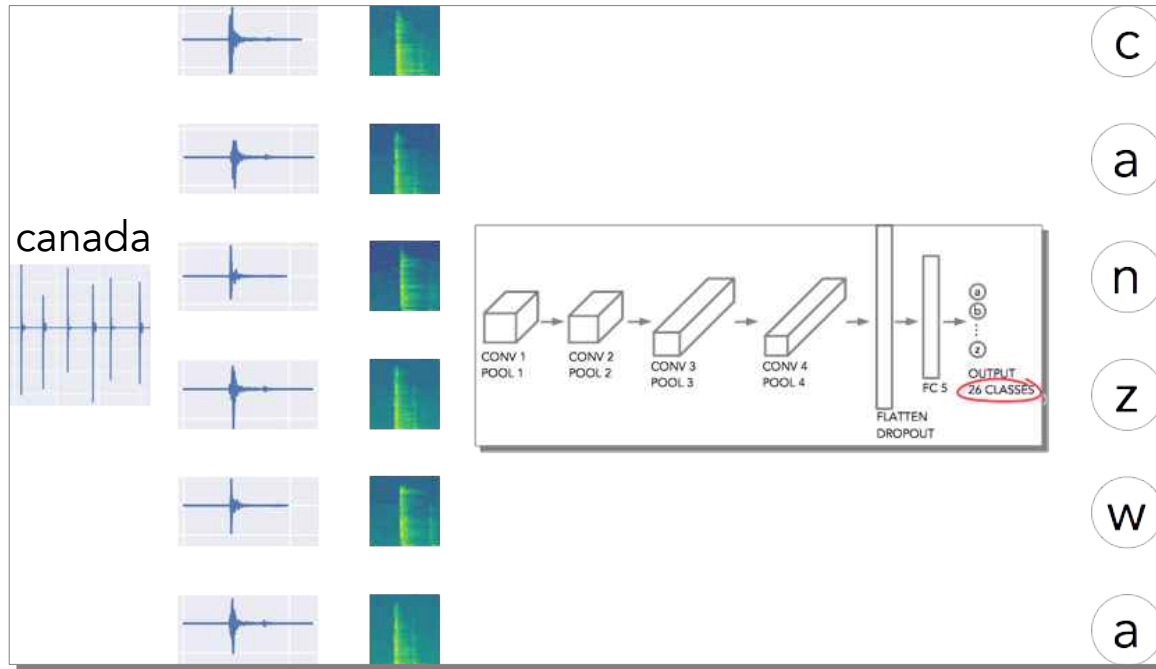
l o k i t a

l o k i t a



What if we pass it
through a spellchecker?!

Improving Model Accuracy



autocorrected
= **spell** (predicted)

→

c

a

n

a

d

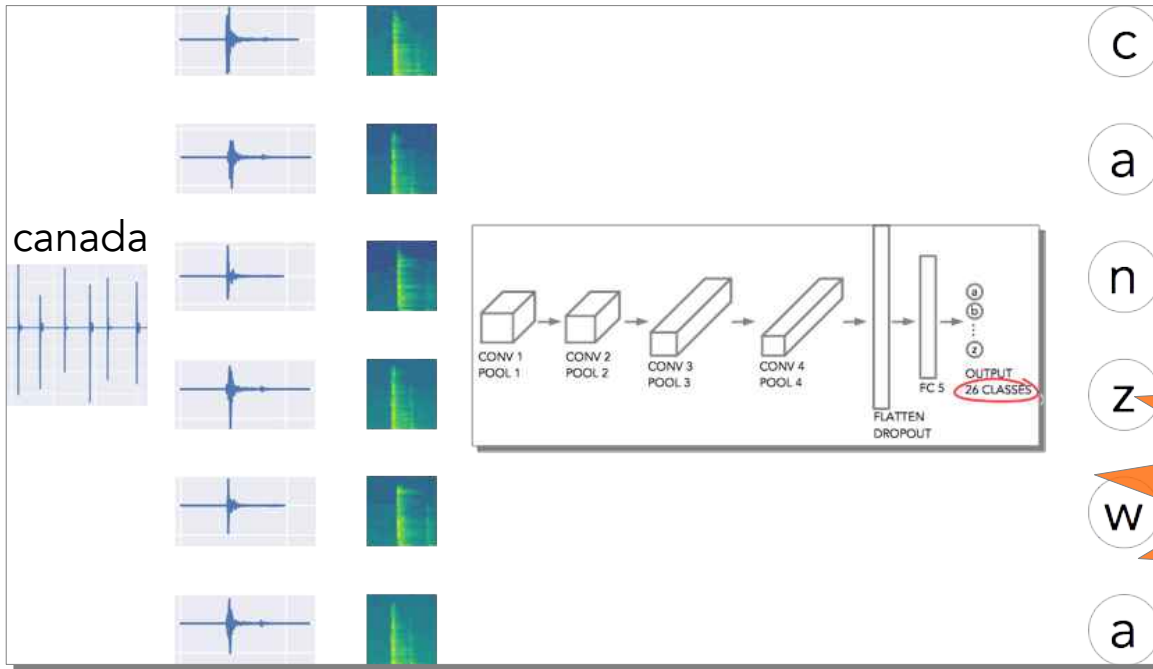
a

CNN Predicted accuracy:
+ Autocorrected accuracy:

Chr Word
48.8 1.5

49.5 8.0

Improving Model Accuracy



autocorrected
= ~~spell~~(predicted)

How about a
RNN instead??

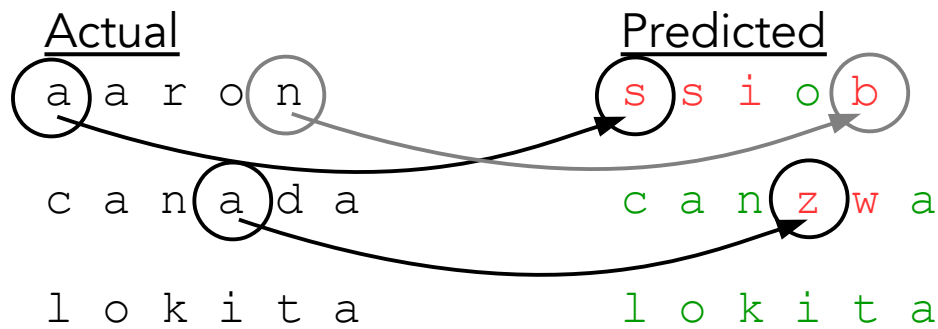
CNN Predicted accuracy:
+ Autocorrected accuracy:

Chr Word
48.8 1.5

49.5 8.0

More Error Analysis

Test Examples

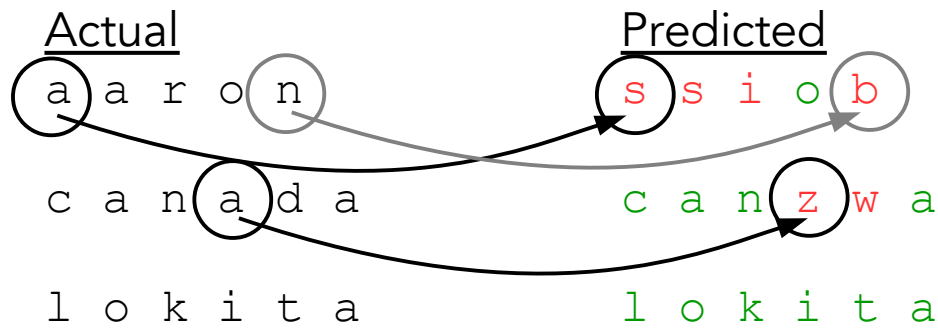


Correct Ones

_ _ _ o _
c a n _ _ a
l o k i t a

More Error Analysis

Test Examples



Correct Ones

_ _ _ o _

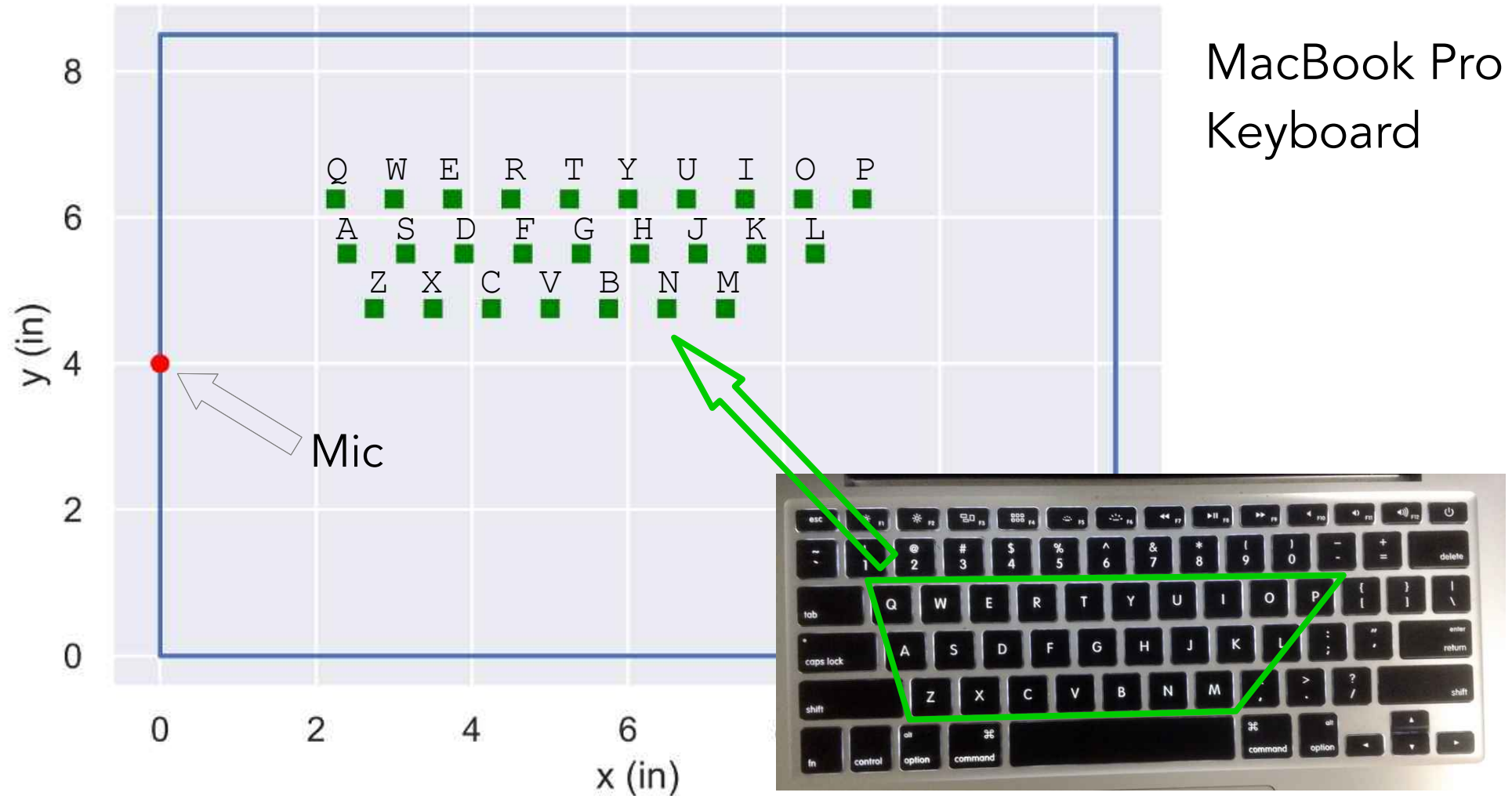
c a n _ _ a

l o k i t a



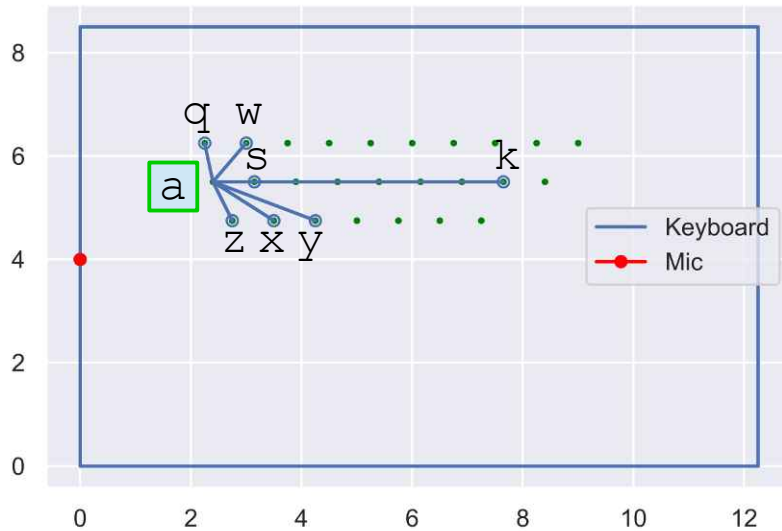
Is the error correlated
to proximity??

More Error Analysis

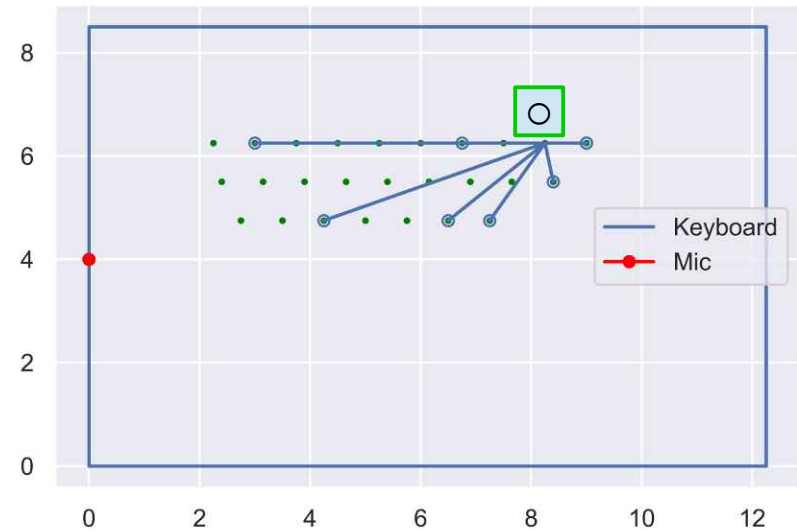


Error Map (Samples)

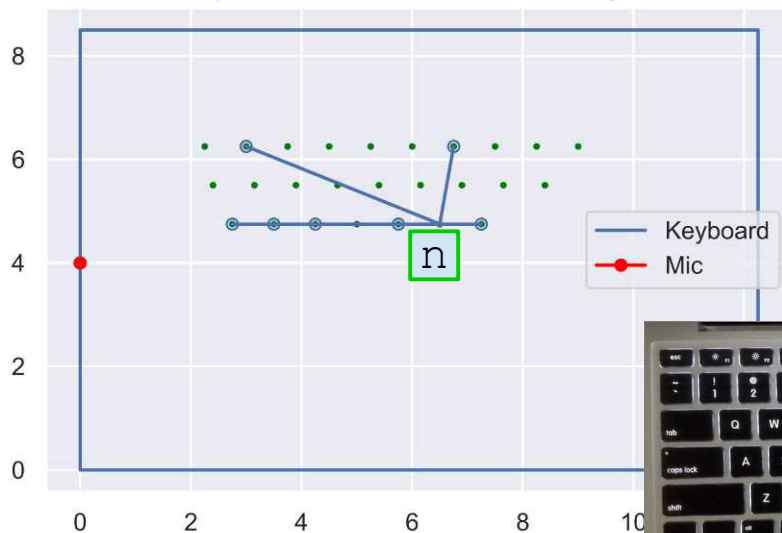
Error Map; Error a = 63 out of 158; Accuracy = 60%



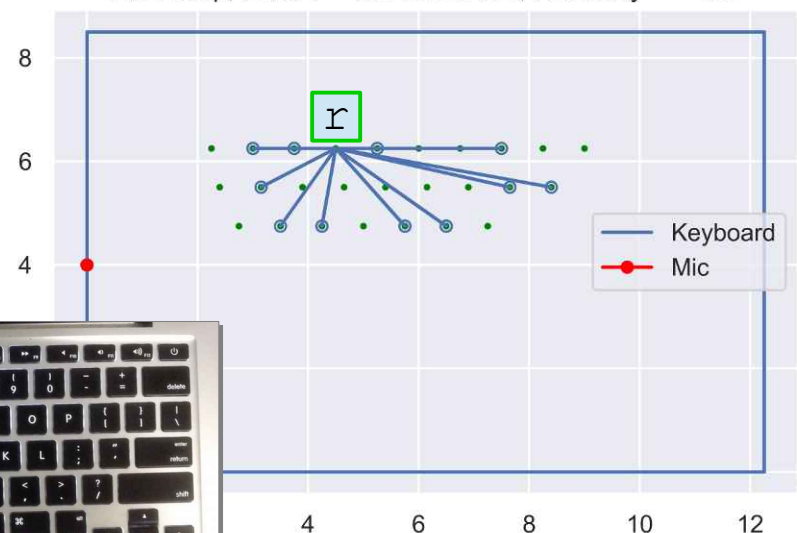
Error Map; Error o = 41 out of 84; Accuracy = 51%



Error Map; Error n = 20 out of 88; Accuracy = 77%

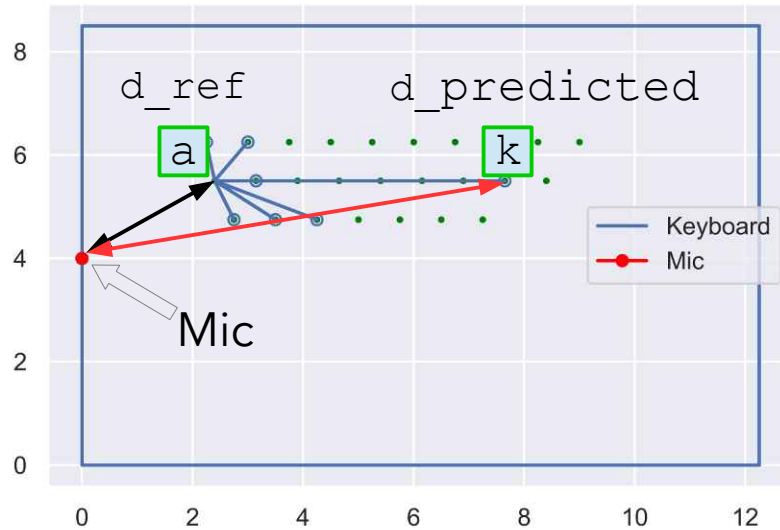


Error Map; Error r = 101 out of 107; Accuracy = 6%



Error Groups

Error Map; Error a = 63 out of 158; Accuracy = 60%



d_ref = dist. of the reference letter from the mic

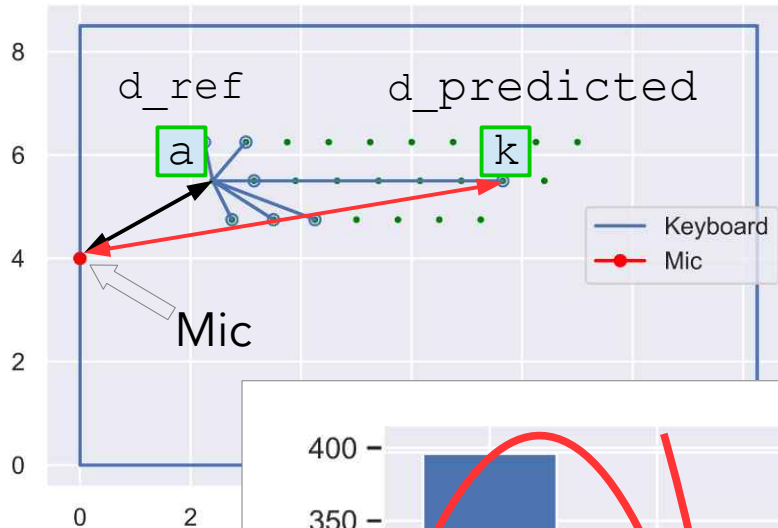
d_predicted = dist. of the predicted letter from the mic

d = `abs(d_predicted - d_ref)`

Bin the errors w.r.t. **d**

Error Groups

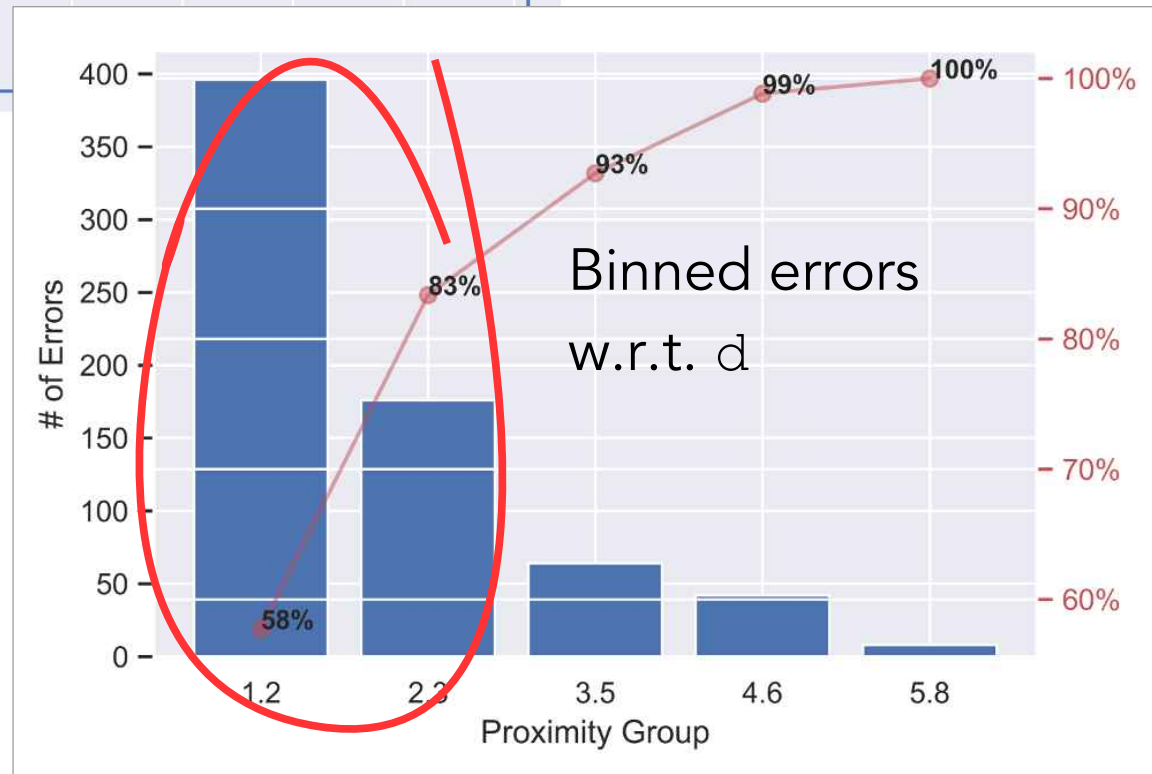
Error Map; Error a = 63 out of 158; Accuracy = 60%



d_{ref} = dist. of the reference letter from the mic

$d_{predicted}$ = dist. of the predicted letter from the mic

$d = \text{abs}(d_{predicted} - d_{ref})$



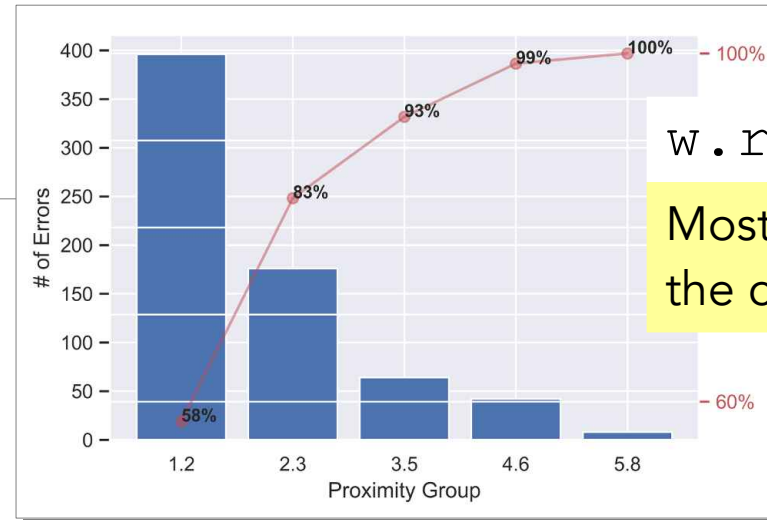
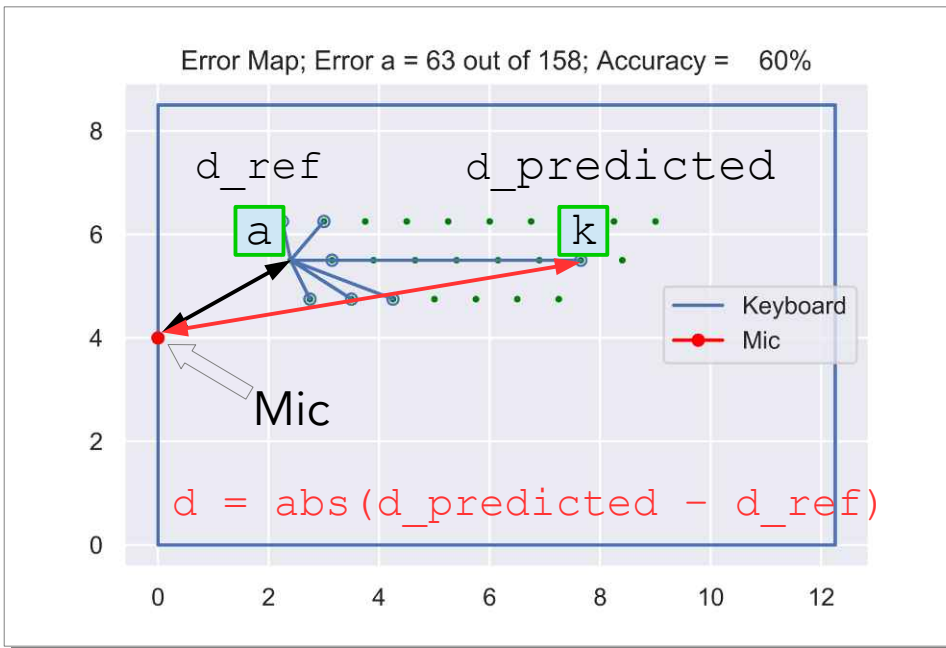
=>

Most errors are from the close proximity

=>

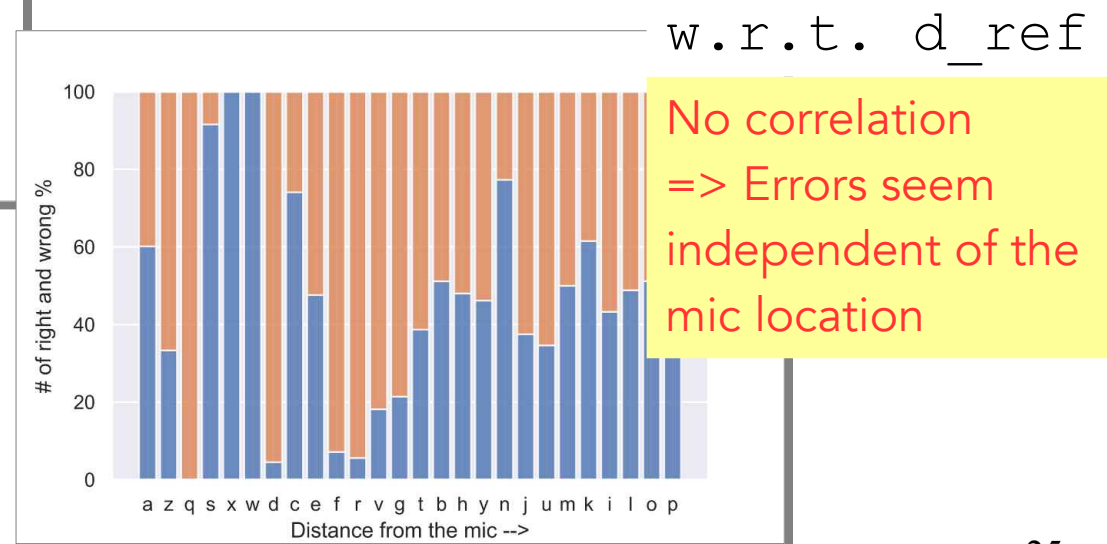
- More data
- Bigger network
- Network architecture that can capture this better

One more thing ...



w.r.t. d

Most errors are from the close proximity



w.r.t. d_{ref}

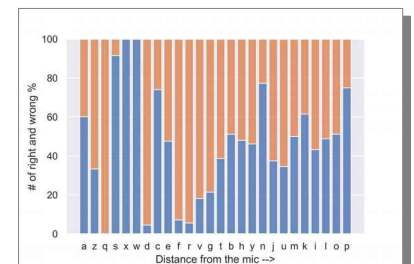
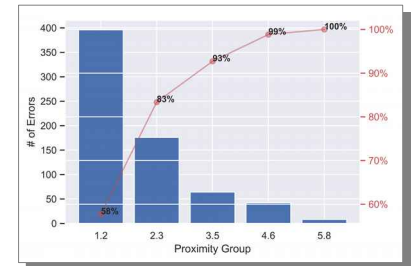
No correlation
=> Errors seem independent of the mic location

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 (8% in this case)
- Error analysis
 - A simple spell check can boost *word-level* accuracy (from 1.5% to 8% in this case)
 - Errors correlate with proximity to the other keys
 - Errors seem independent of the mic location



	Chr	Word
<u>CNN Predicted</u> accuracy:	48.8	1.5
<u>+ Autocorrected</u> 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 [?] **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 [?] **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