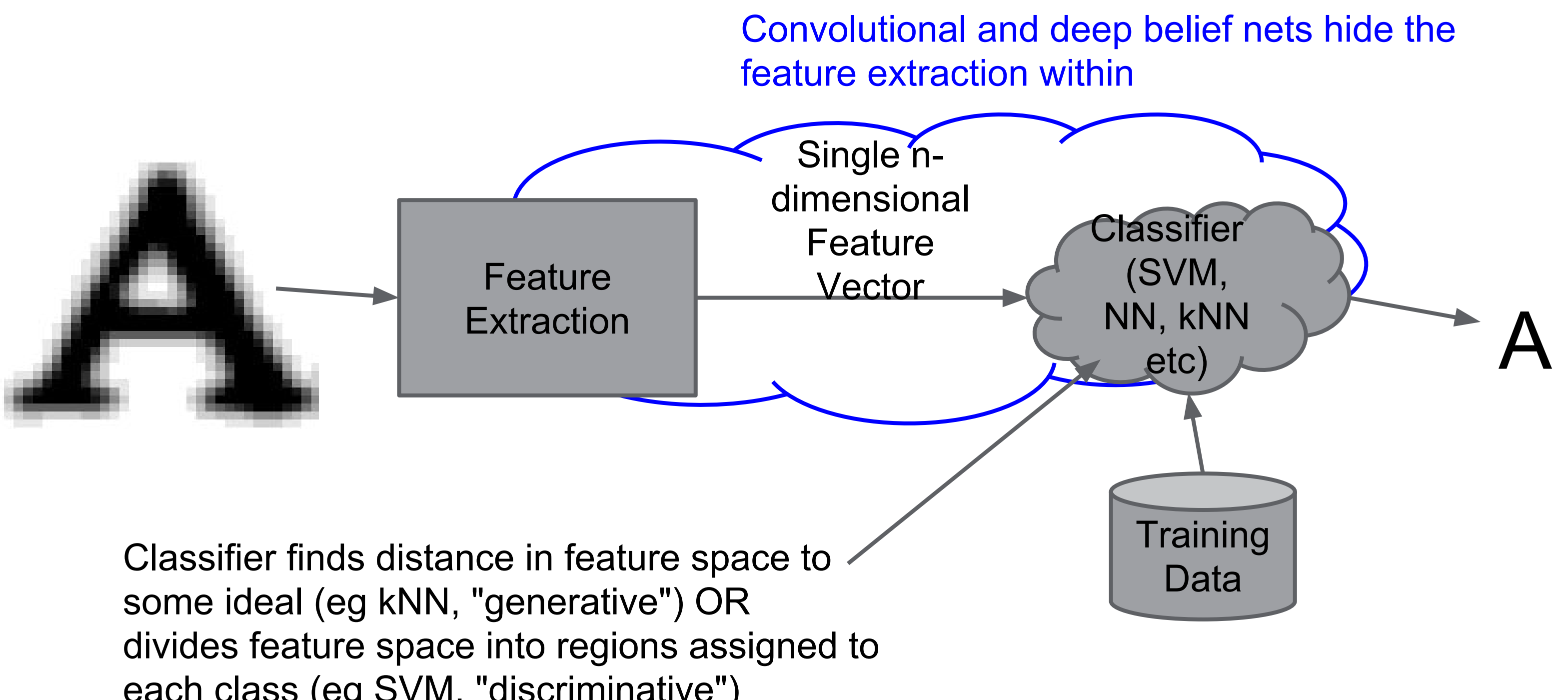
3. Features and Character Classifier

The components that made Tesseract successful

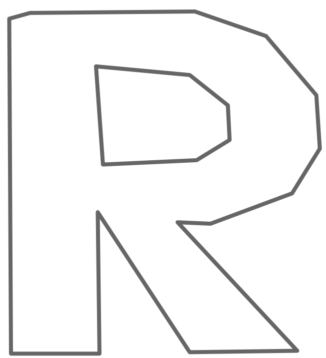
Ray Smith, Google Inc.

Background: Classical character classification

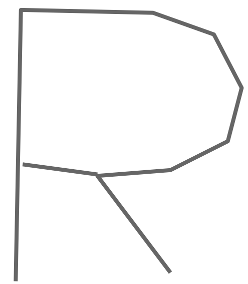


Motivation: How to extract features from Outlines?

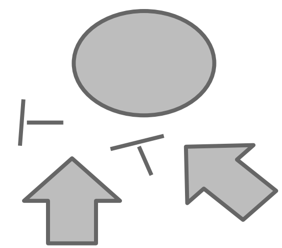
Outline



Skeleton

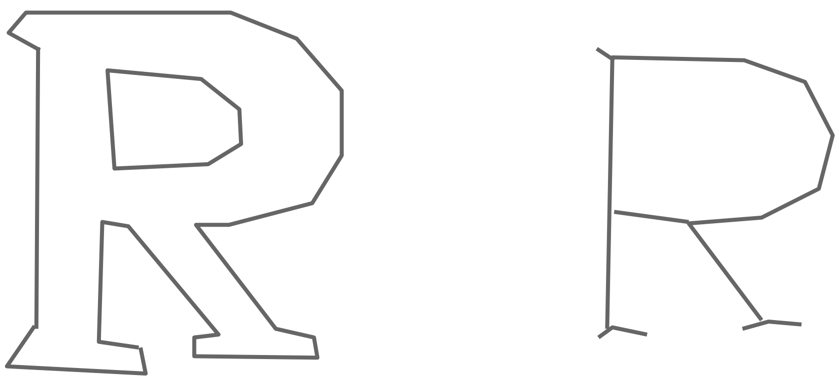


Topological Features



Skeletonization is Unreliable

Outline: Serifed   Skeleton: Decorated



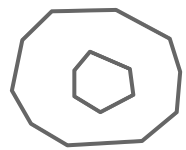
Arrrrh!

Lesson: If there are a lot of papers on a topic, there is most likely no good solution, at least not yet, so try to use something else.

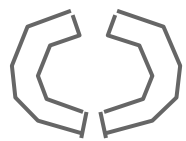
Topological features are Brittle

Damage to 'o' produces vastly different feature sets:

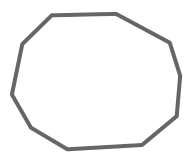
Standard 'o'



Broken 'o'



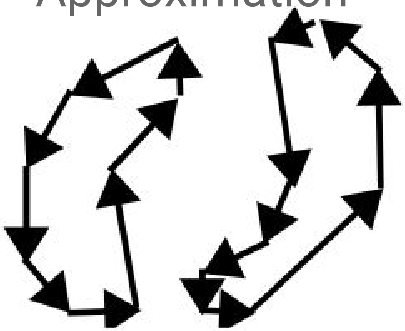
Filled 'o'



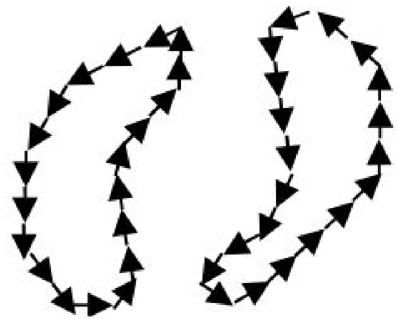
Lesson: Features must be as invariant as possible to as many as possible of the expected degradations.

Shrinking features and inappropriate statistics

Segments of the polygonal Approximation



Even smaller features



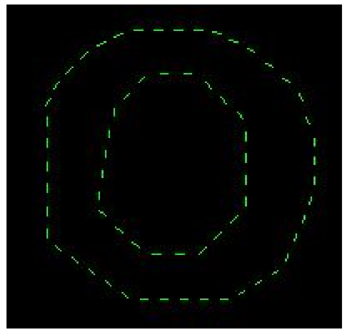
Statistical: $$argmax(k)\prod_{l,i}\frac{1}{\sigma_{ijk}}\exp[-\frac{1}{2}(\frac{x_{il}-\mu_{ijk}}{\sigma_{ijk}})^2]$$

Geometric: $$argmin(k)\frac{1}{M+J_k}(\sum_{l,i}(x_{il}-\mu_{ijk})^2+\sum_{j,i}(x_{il}-\mu_{ijk})^2)$$

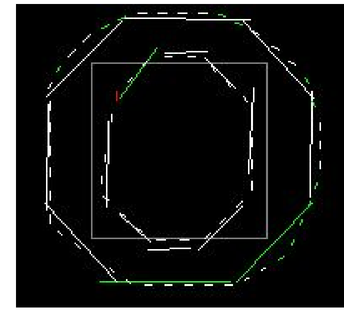
Lesson: Statistical Independence is difficult to dodge.

Inspiration: Even on a damaged character, most features still match if they are small!

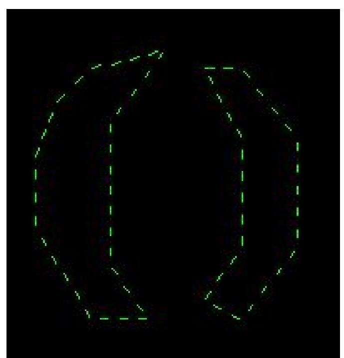
Features of clean ‘o’



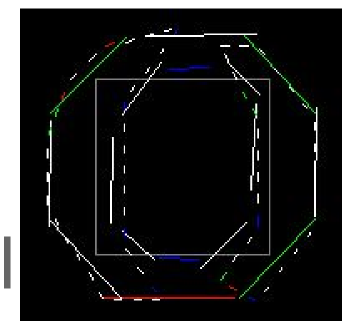
Matched with best template



Features of broken ‘o’



Mostly still matches

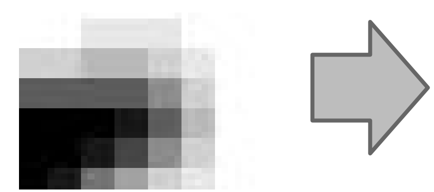


Interlude: Comparison with Recent Work

(Convolutional) Deep Belief nets:

1 pixel = 1 feature dimension

1 character (eg 32x32) = ~1K dimension feature vector

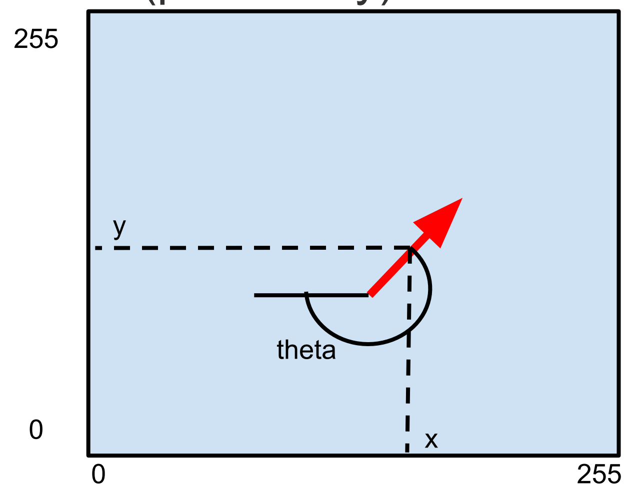


1.0
1.0
0.7
0.7
0.7
1.0
0.6
0.6
0.5
0.5
0.6
0.7
...

- Features are learned
- Usually edges
- Statistical dependence between pixels must also be learned: Purpose of network depth

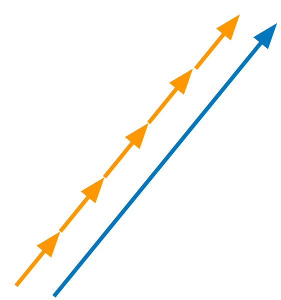
Features extracted from the unknown: 3D INT_FEATURE_STRUCT

- Multiple features extracted from a single unknown
- Each feature is a short, **fixed length**, directed, line segment, with (x,y) position and theta direction making a 3-D feature vector (x, y, theta) from an integer space [0, 255]
- Direction is measured (perversely) from the negative x-axis!



Features in the training data: 4D (hence Tesseract) INT_PROTO_STRUCT

- Elements of the polygonal approximation, clustered within a character/font combination.
- x,y position, direction, **and length** (as a multiple of feature length)



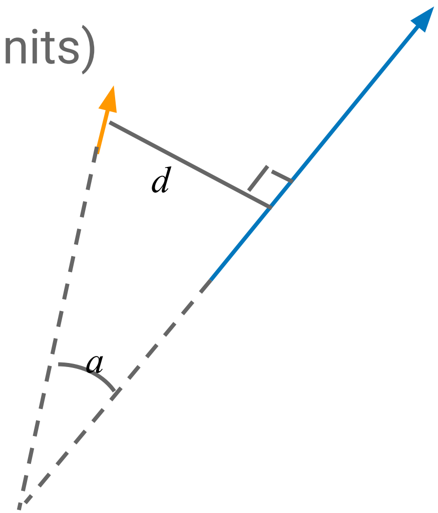
The Distance function: Single Feature to Single Proto

d = perpendicular distance of feature f from proto p

a = angle between feature f and proto p

Feature distance $d_{fp} = d^2 + a^2$ (in appropriate units)

Feature evidence e_{fp} = 1* / (1 + $kd_{fp}{}^2$)

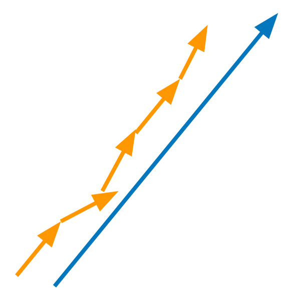


*In the actual implementation, everything is scaled up and run in integer arithmetic until the final result.

Feature Evidence and Proto Evidence
(For a single Font Config of a single Character Class)

Feature evidence $e_f = \max\limits_{\text{p in config}} e_{fp}$

Proto evidence $e_p = \sum\limits_{\text{top } l_p} e_{fp}$ (Proto p is of length l_p)



The CN (Character Normalization) Feature

Single 4-D feature for each unknown:

- Y-Position relative to baseline
- Outline Length (in normalized space)
- 2nd x-moment
- 2nd y-moment

The Distance Function: Unknown char to Prototype

$$d = 1 - \max \frac{\sum_f e_f + \sum_p e_p}{N_f + \sum_p l_p} \qquad d' = \frac{d l_o + kc}{l_o + k}$$

Feature-proto distance *CN correction*

l_o = Length of outline

c = Char position feature distance (CN feature)

k = classify_integer_matcher_multiplier (arbitrary constant = 10)

Rating = $d' l_o$

Certainty = $-20d'$

Rating *and* certainty? Why not just a “probability?”

- Rating = Distance * Outline length
    - Total rating over a word (or line if you prefer) is normalized
    - Different length transcriptions are fairly comparable
- Certainty = -20 * Distance
    - Measures the absolute classification confidence
    - Surrogate for log probability and is used to decide what needs more work.
- Comparing products of probability or sums of log probs of different length requires a non-rigorous hack anyway.

Now it's Too Slow!

~2000 characters per page x
~100 character classes (English) x
32 fonts x
~20 prototype features x
~100 unknown features x
3 feature dimensions

= 38bn distance calculations per page...

Now it's Too Slow!

~2000 characters per page x
~100 character classes (English) x
32 fonts x
~20 prototype features x
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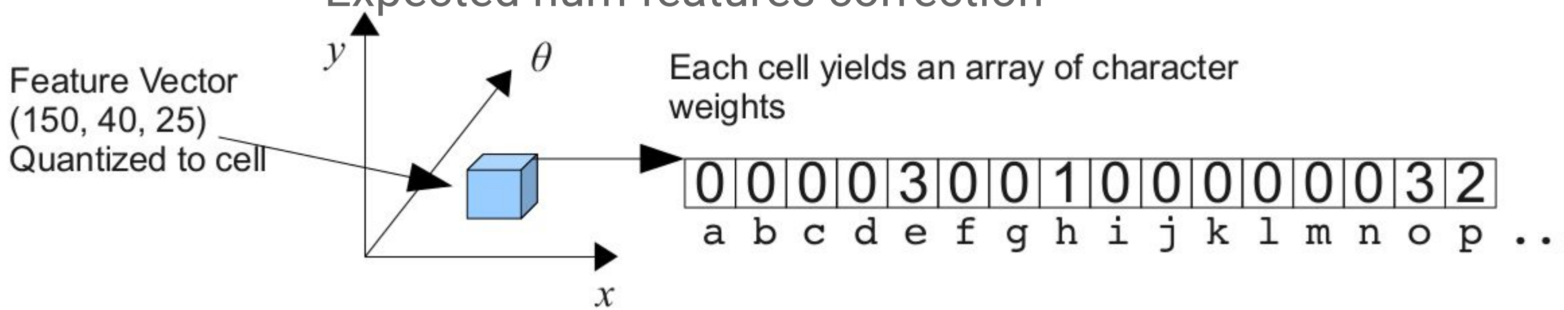
3 feature dimensions

= 38bn distance calculations per page...
... **on a 25MHz machine.**

Speeding up kNN: The Class Pruner

- Quantize feature space down from 256^3 to 24^3.
- Create inverted index: 3-D feature -> List of matching classes.
- Equivalent to a linear classifier with binary feature vector with 13824 dimensions.
- Fast, (~70 µs for Eng) but O(<num features> * <num classes>)
- Low top-n error rate (~0.01-0.5%), with low n (3-5)/110 even on unseen fonts, rising to 8% top-n on vastly different fonts.
- Top-1 error rate not so good at 8% typical.

Secret sauces: 2-bit weights and spreading from the mean of the clusters.
Expected num features correction



Interlude: Comparison with Recent Work

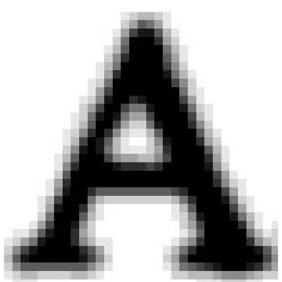
Histogram of Gradients

- Quantize character area
- Compute gradients within
- Histograms of gradients map to fixed dimension feature vector
- Remarkably similar to class pruner

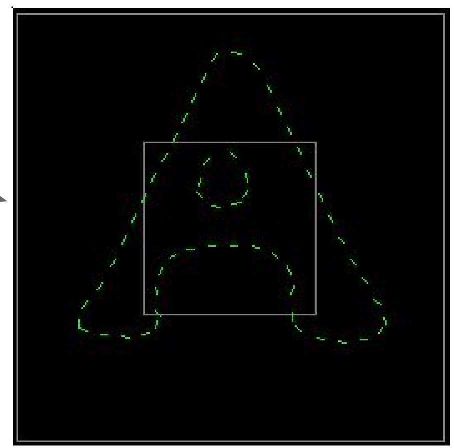
Interlude: Comparison with Recent Work: kNN

- Much has been published on speeding up kNN, eg randomized hashing, locality sensitive hashing etc.
- Much has also been published on indexing to speed-up recognition.

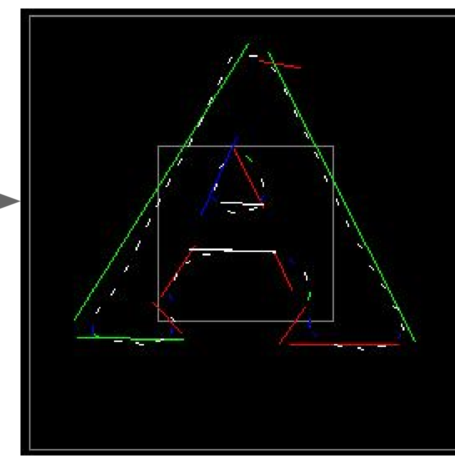
Real Classification Example



Multiple (varied) features, each of 3 dimensions (x, y, direction), of unit length.



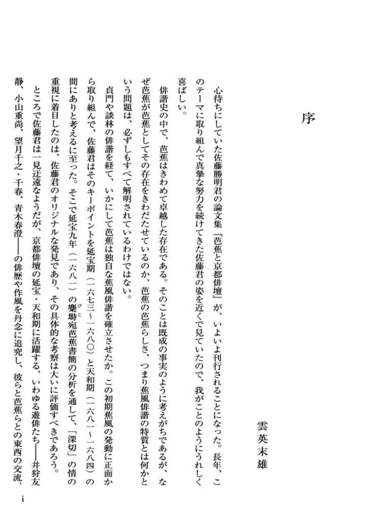
Classifier measures overall geometric similarity to closest character/font combination (kNN, generative).



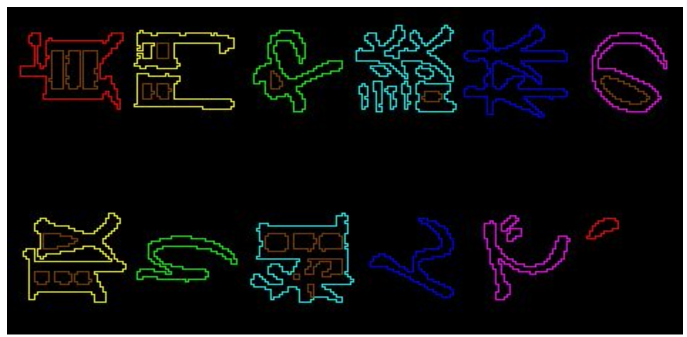
Normalization

There are many stages of Normalization in Tesseract:

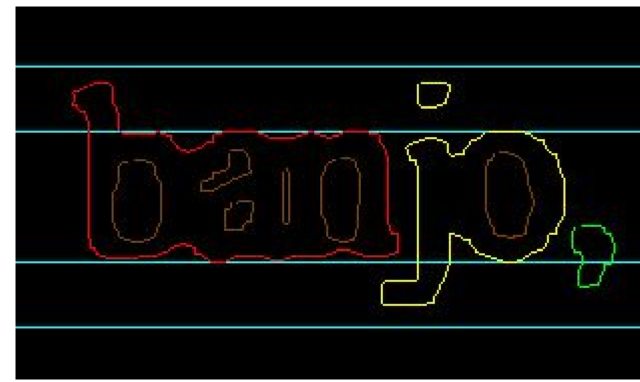
Image



Rotated



Word BLN



Normalization Rules

Image:

- Only the API knows of possible scaling and cropping of the source image. Inside Tesseract, the image is not touched.

C_BLOBs:

- Constrained to be pixel-oriented, they cannot be scaled or rotated other than by multiples of 90 degrees.
- The only difference between C_BLOBs and the image is a possible block rotation to keep textlines horizontal.

TBLOBs:

- Begin life as Word-Baseline-Normalized, these are the input to the chopper and classifier.
- There may be an additional rotation for classification. (CJK)

Classifier Normalizations

Beginning with a word-baseline-normalized TBLOB (possibly rotated again to be the right way up) the classifier further normalizes for feature extraction:

- Baseline Norm: No further scaling, but x-center the character in the classifier feature space.
- Character Norm: Center the character in the feature space by centroid, and scale by 2nd moments anisotropically.
- Non-linear Norm: Scale to preserve edge density in a non-linear way to fill the feature space in some sense. (Not used, but maybe in the future.)

Applications of different Normalizations

Baseline/x-height

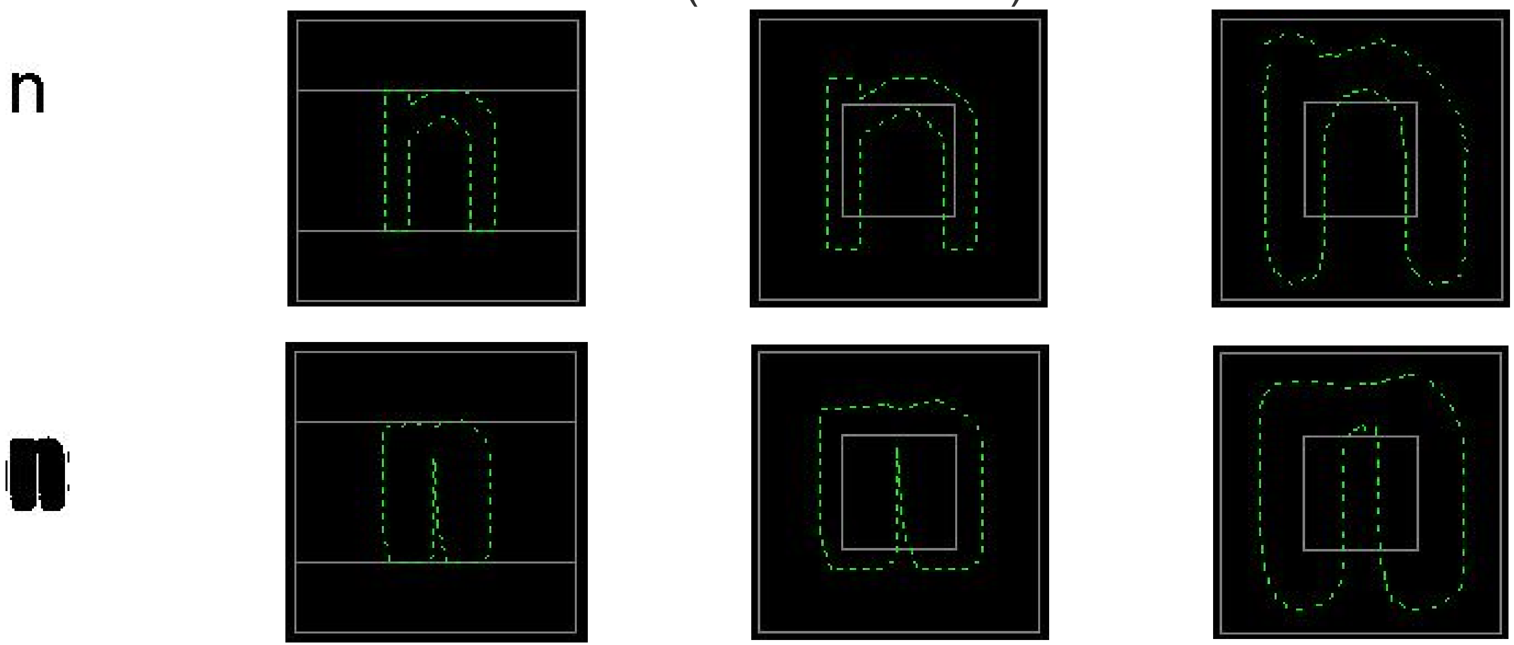
- Used by Adaptive classifier
- Align on x centroid, y on baseline
- Scale uniformly by xheight.
- Sees sup/super as different classes.
- Ignores speckle noise well.

Character Moments

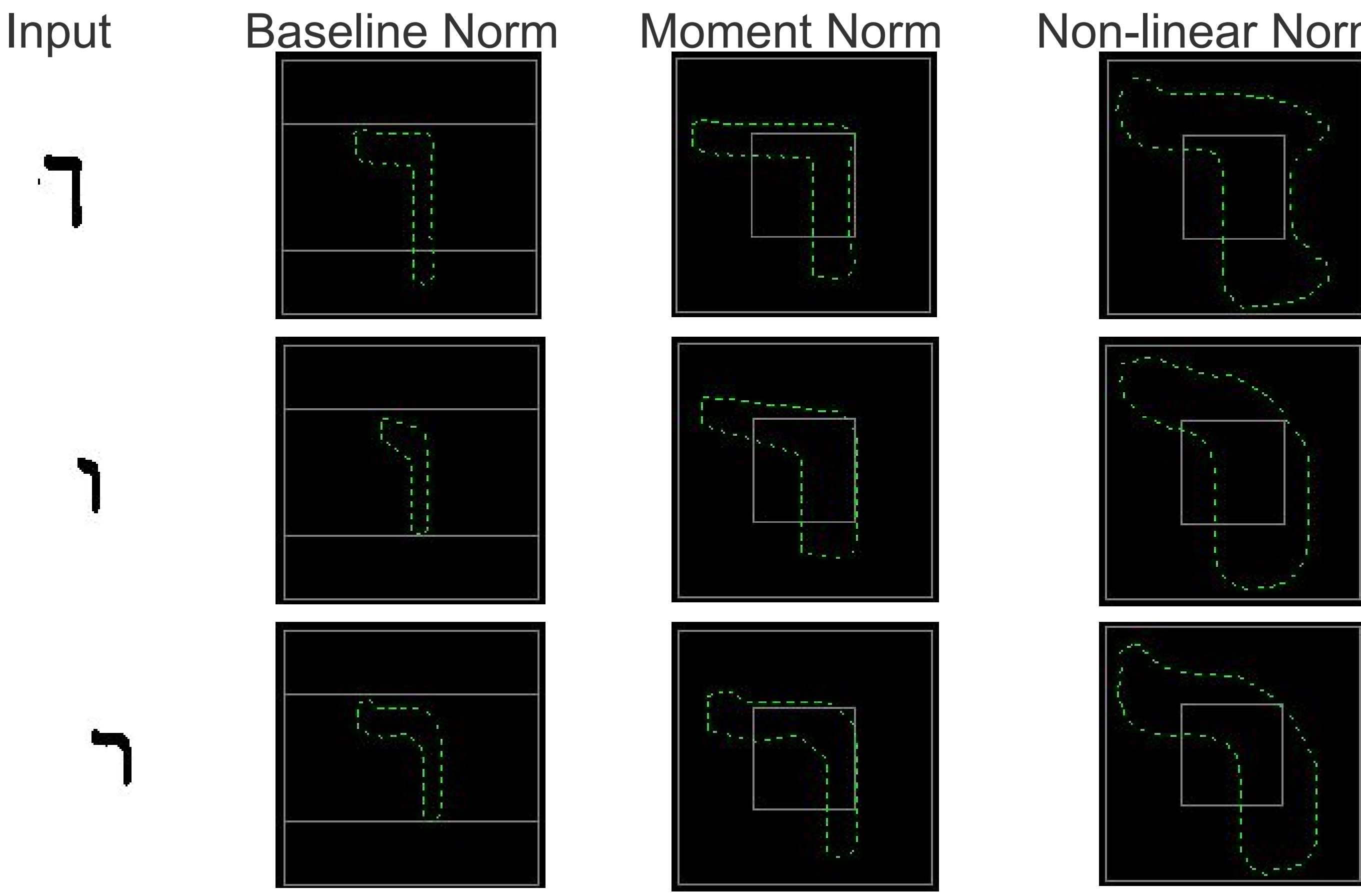
- Used by static classifier.
- Align on Centroid
- Scale by 2nd moments independently in x and y
- Eliminates a lot of font variation.
- Makes '-' '.' '_' 'l' ambiguous.
- Makes sub/superscript appear same as normal
- Fooled by speckle noise

Character-level Normalization

Input | Baseline-norm | Moment-norm (aka char-norm) | Non-linear norm

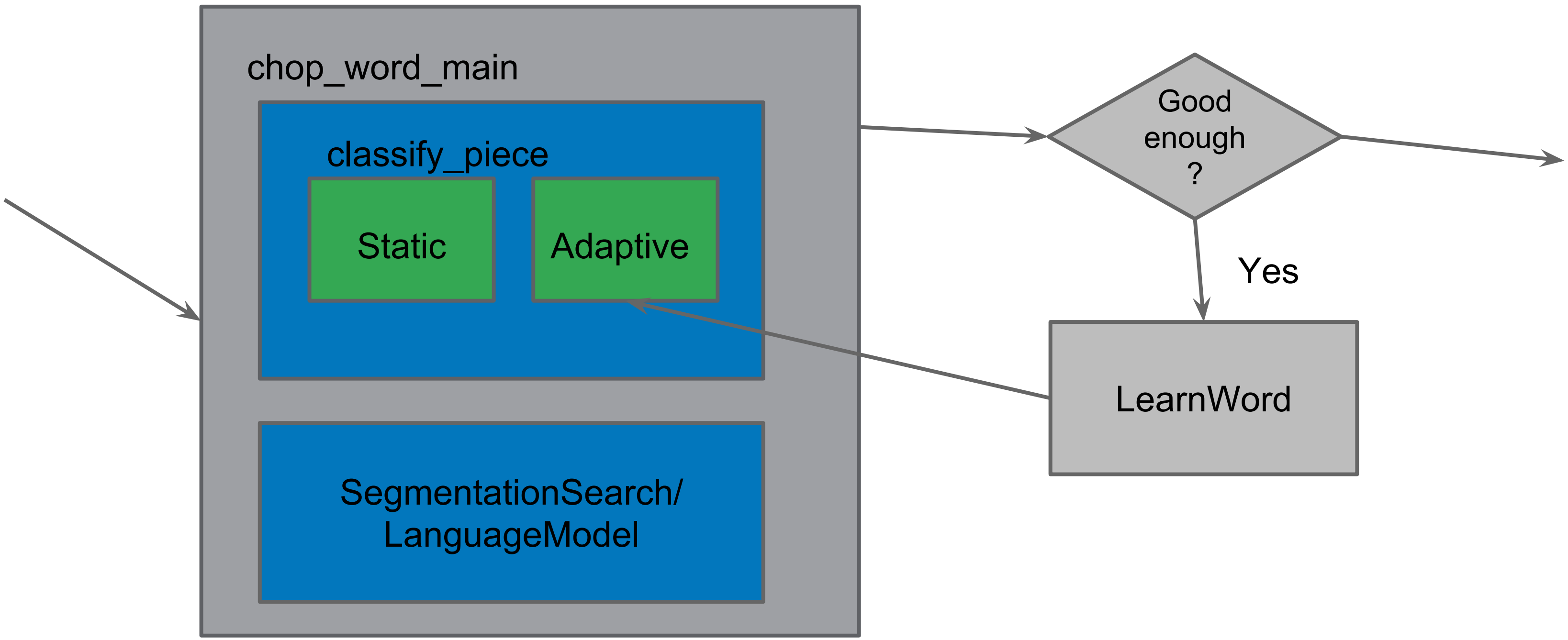


Character-level Normalization (Hebrew example)



Adaptive Classifier: On-the-fly Adaption

classify_word_pass1



Thanks for Listening!

Questions?