Iterated Document Content Classification

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Motivation

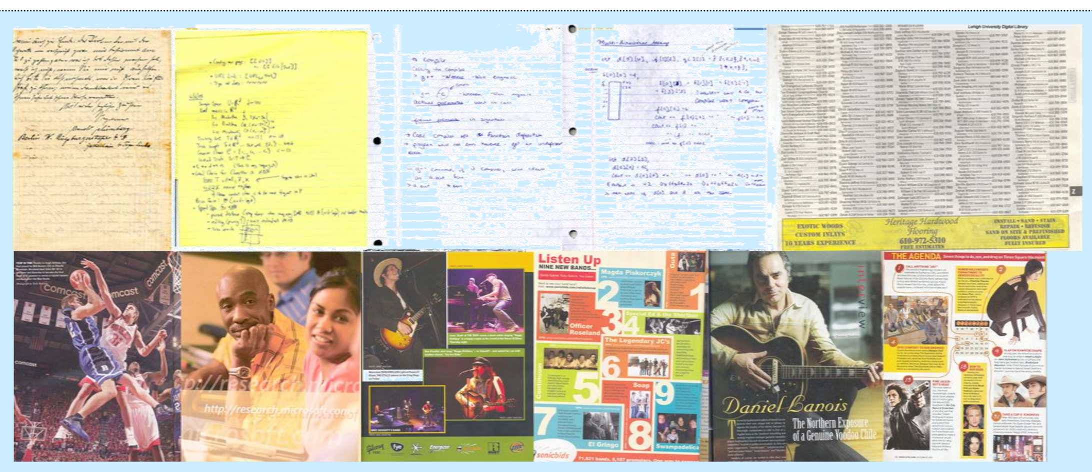
Our previous methods classified each individual pixel separately

This policy allows content classes to vary frequently within small regions

Local uniformity is required for down-stream process

Post-classification method is chosen to enforce local uniformity without imposing arbitrary shapes

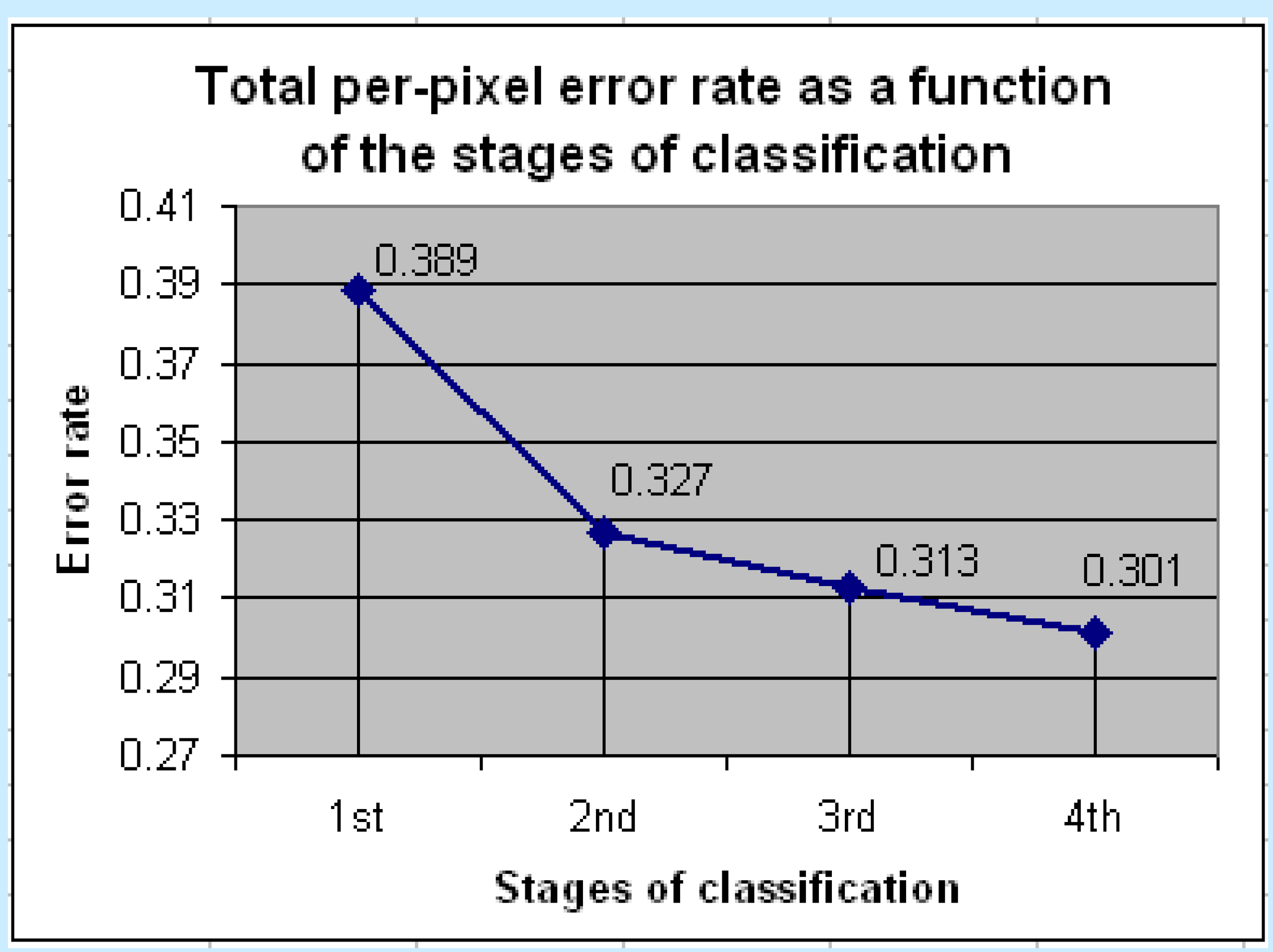
Vast Variety of Images



Training set : 33 images, 87M pixels

Test set : 83 images, 239M pixels

Result: 23% drop in error



Task: Find Uniform Regions of Content in Scanned Document Images

Original image

Output of 1st stage

Color Codes for Content	
Blue: Machine Print	White: Blank
Aqua: Photograph	Purple: Handwriting

Training and test samples are single pixels

Avoids arbitrary, e.g. rectangular, shapes of zones

Classification is by approximate Nearest Neighbors

In output, each content type can be labeled with a color and displayed accordingly

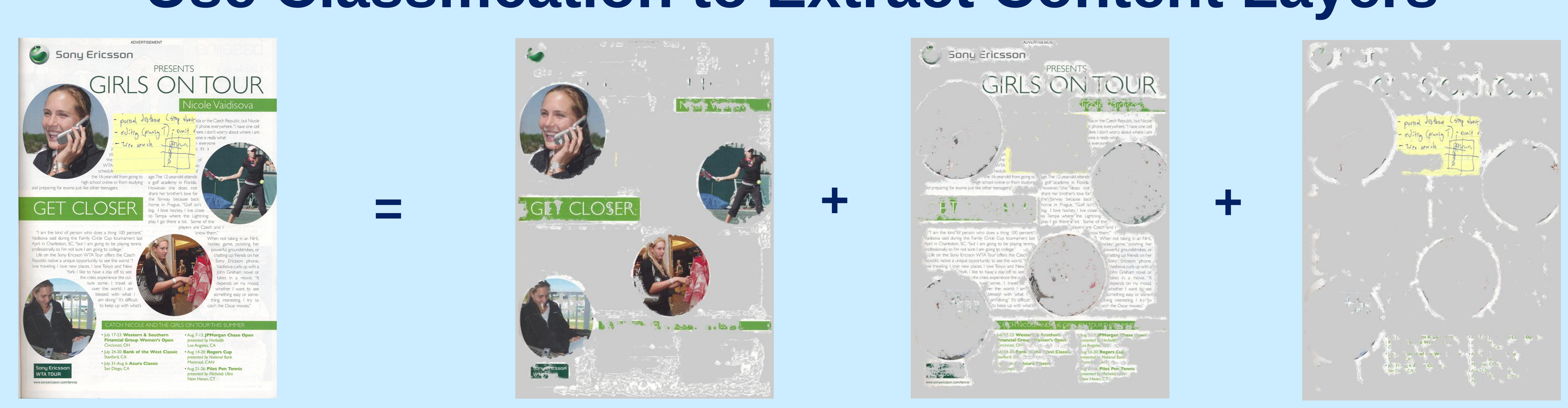
Refinement: Iterated Classification

The 1st-stage classification yields areas where several content classes are mixed together

In real content, almost all small local regions are of uniform class

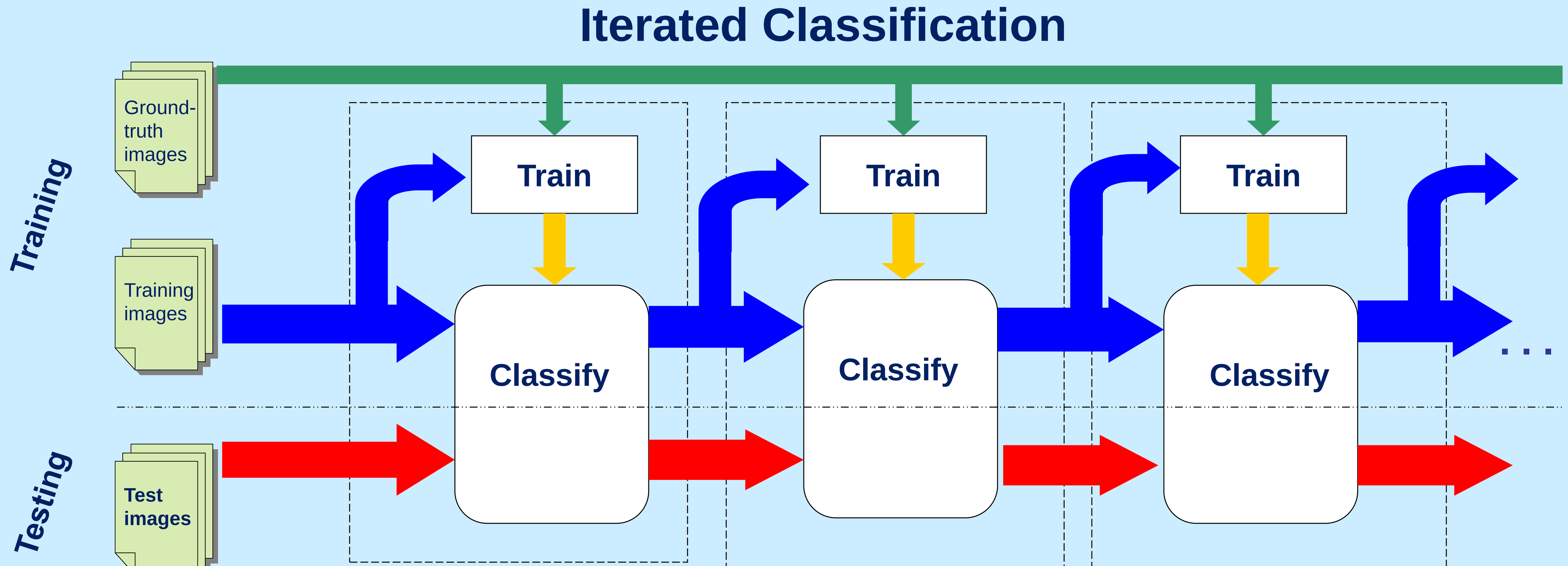
Improve result by post-classification

Use Classification to Extract Content Layers



Photograph (PH) **Machine Print (MP)** **Handwriting (HW)**

Iterated Classification



Instability Issue

In one experiment, at the 9th stage, large solid regions of HW were misclassified as MP.

Promising workarounds:

(1) Drop a training image whenever its error rate rises

(2) Increase the radius of the features

Future Work

Classification with features over a range of scales

Seek guaranteed solutions to the instability issue

Increase the number of iterations

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