Deep Learning

Advanced Machine Learning
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Basics of Digital Imaging

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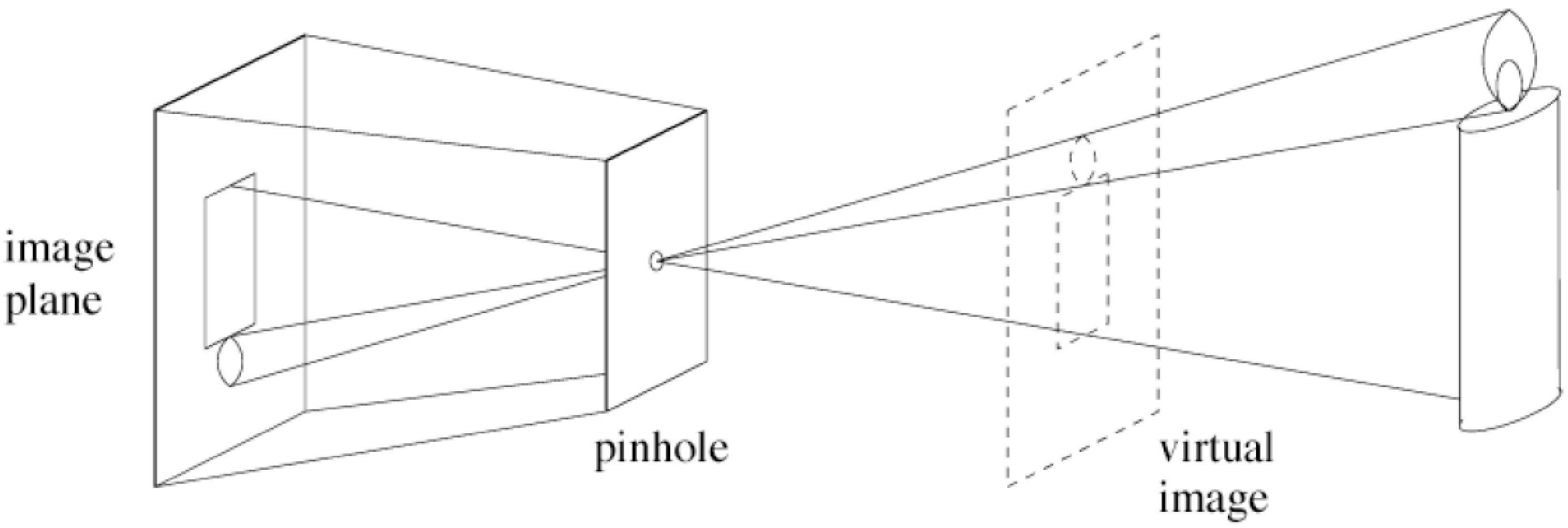
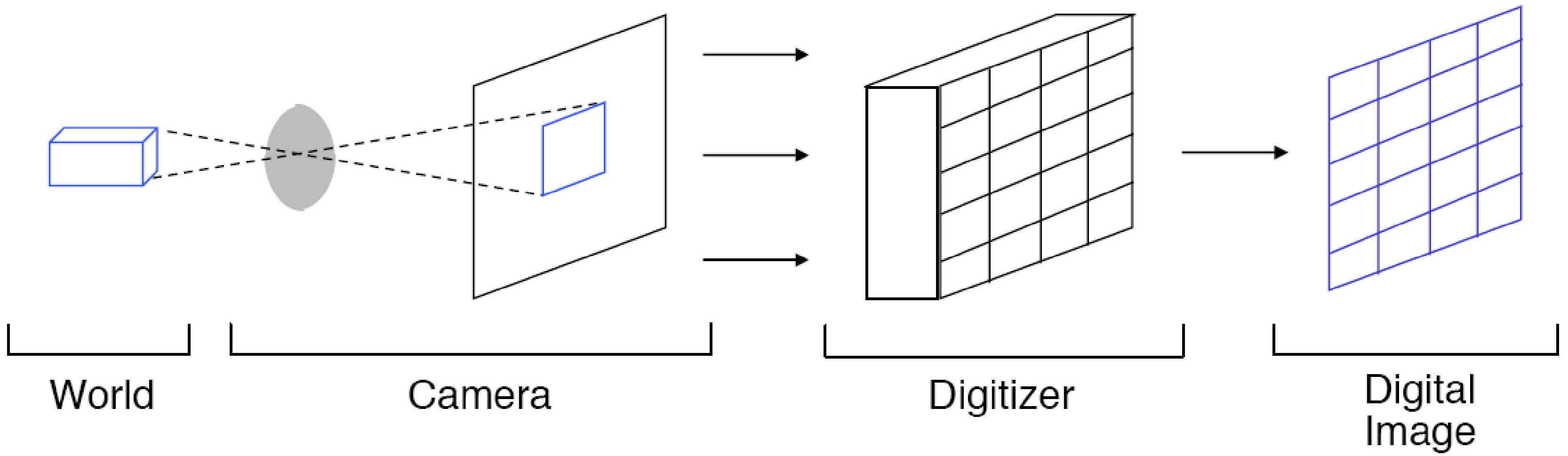
Pinhole Camera (Model)

- (simple) standard and abstract model today
  - box with a small hole in it



Digital Images

- Imaging Process:
  - (pinhole) camera model
  - digitizer to obtain digital image



Digital Image Processing

- Image Filtering
  - take some local image patch (e.g. 3x3 block)
  - image filtering: apply some function to local image patch

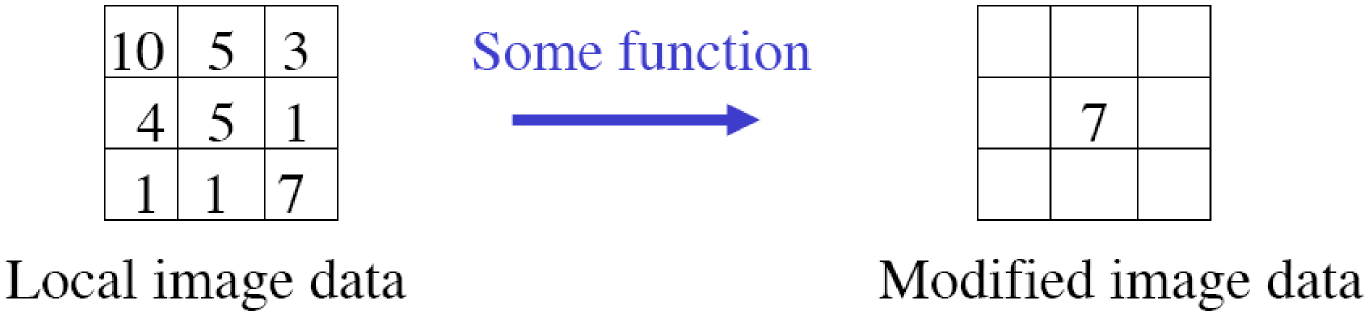


Image Filtering

- Some Examples:
  - what assumptions are you making to infer the center value?

3	3	3
3	?	3
3	3	3

3

3	4	3
2	?	5
5	4	2

3 or 4

Image Filtering: 2D Signals and Convolution

- Image Filtering
  - to reduce noise,
  - to fill-in missing values/information
  - to extract image features (e.g. edges/corners), etc.

$$\begin{array}{|c|c|c|}\hline 2 & 3 & 3 \\ \hline 3 & 20 & 2 \\ \hline 3 & 2 & 3 \\ \hline \end{array} \longrightarrow \begin{array}{|c|c|c|}\hline 2 & 3 & 3 \\ \hline 3 & 3 & 2 \\ \hline 3 & 2 & 3 \\ \hline \end{array}$$

- Simplest case:
  - linear filtering: replace each pixel by a linear combination of its neighbors

- 2D convolution (discrete):

$$f[m,n] = I \otimes g = \sum_{k,l} I[m-k, n-l] g[k,l]$$

  - discrete Image: *I[m,n]*
  - filter 'kernel': *g[k,l]*
  - 'filtered' image: *f[m,n]*

$$\underset{f[m,n]}{\begin{array}{|c|c|c|}\hline & & \\ \hline & 18 & \\ \hline & & \\ \hline \end{array}} = \underset{I[k,l]}{\begin{array}{|c|c|c|}\hline 8 & 5 & 2 \\ \hline 7 & 5 & 3 \\ \hline 9 & 4 & 1 \\ \hline \end{array}} \otimes \underset{g[k,l]}{\begin{array}{|c|c|c|}\hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline \end{array}}$$

can be expressed as matrix multiplication!

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Image Filtering: 2D Signals and Convolution

- 2D convolution (discrete): $f[m,n] = I \otimes g = \sum_{k,l} I[m-k, n-l] g[k,l]$
  - discrete Image: *I[m,n]*
  - filter 'kernel': *g[k,l]*
  - 'filtered' image: *f[m,n]*

$$f[m,n] \quad I[k,l] \quad g[k,l]$$

$$\begin{array}{|c|c|c|} \hline & & \\ \hline & 18 & \\ \hline & & \\ \hline \end{array} = \begin{array}{|c|c|c|} \hline 8 & 5 & 2 \\ \hline 7 & 5 & 3 \\ \hline 9 & 4 & 1 \\ \hline \end{array} \otimes \begin{array}{|c|c|c|} \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline \end{array}$$

l k (m, n) l k

$$= \sum_{\substack{-1 < k < +1 \\ -1 < l < +1}} I[m-k, n-l] g[k,l]$$ (m, n)

- mirror the filter (k and l)
- swipe it across the image
- multiply and sum

$$= I[m+1, n+1] g[-1,-1] \qquad (k=-1, l=-1)$$

$$+ I[m+1, n] g[-1, 0] \qquad (k=-1, l=0)$$

$$+ I[m+1, n-1] g[-1, +1] \qquad (k=-1, l=+1)$$

$$+ \ldots$$

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Image Filtering: 2D Signals and Convolution

- 2D convolution (discrete): $f[m,n] = I \otimes g = \sum_{k,l} I[m-k, n-l]g[k,l]$
  - discrete Image: *I[m,n]*
  - filter ‘kernel’: *g[k,l]*
  - ‘filtered’ image: *f[m,n]*

$$\underset{f[m,n]}{\begin{array}{|c|c|c|}\hline & & \\ \hline & 18 & \\ \hline & & \\ \hline \end{array}} = \underset{I[k,l]}{\begin{array}{|c|c|c|}\hline 8 & 5 & 2 \\ \hline 7 & 5 & 3 \\ \hline 9 & 4 & 1 \\ \hline \end{array}} \otimes \underset{g[k,l]}{\begin{array}{|c|c|c|}\hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline -1 & 0 & 1 \\ \hline \end{array}}$$

- special case:
  - convolution (discrete) of a 2D-image with a 1D-filter

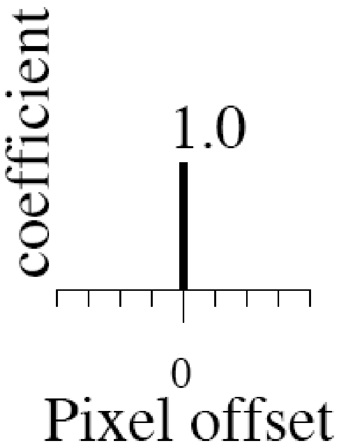
$$f[m,n] = I \otimes g = \sum_{k} I[m-k, n]g[k]$$

$$\underset{g[k]}{\begin{array}{|c|}\hline -1 \\ \hline 0 \\ \hline 1 \\ \hline \end{array}}$$

Linear Filtering (warm-up slide)

$$f[m,n] = I \otimes g = \sum_{k} I[m-k,n]g[k]$$

original



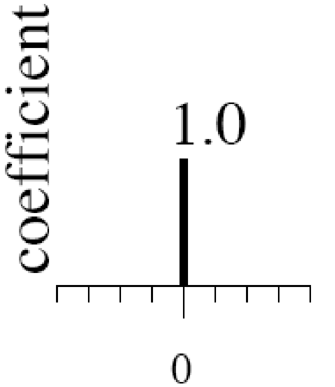
$= ?$

$I \quad \otimes \quad g \quad = f$

Linear Filtering (warm-up slide)

$$f[m,n] = I \otimes g = \sum_k I[m-k,n]g[k]$$

original

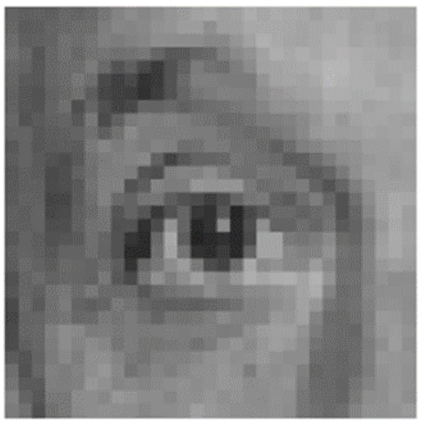


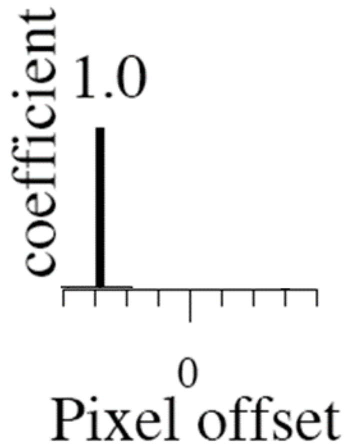
Filtered
(no change)

$$I \qquad \otimes \qquad g \qquad = f$$

Linear Filtering

$$f[m,n] = I \otimes g = \sum_k I[m-k,n]g[k]$$





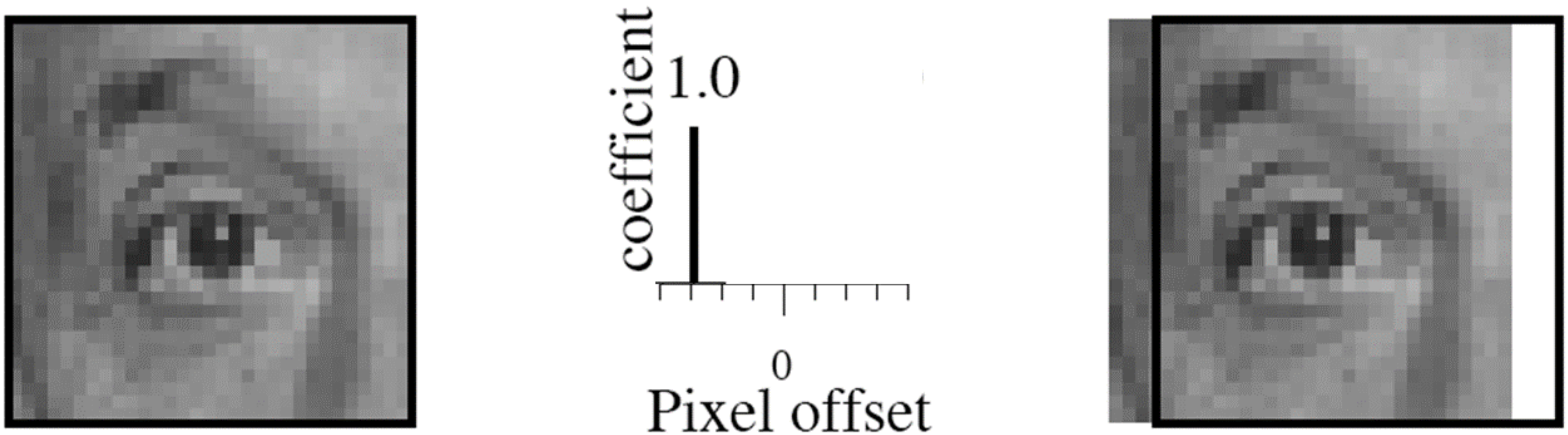
?

original

I $\otimes$ g $= f$

Linear Filtering

$$f[m,n] = I \otimes g = \sum_{k} I[m-k,n]g[k]$$



original

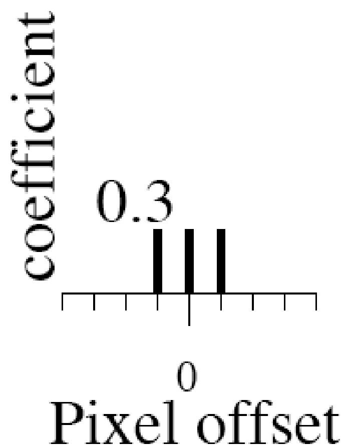
shifted

$I \quad \otimes \quad g \quad = f$

Linear Filtering

$$f[m,n] = I \otimes g = \sum_k I[m-k,n]g[k]$$

original



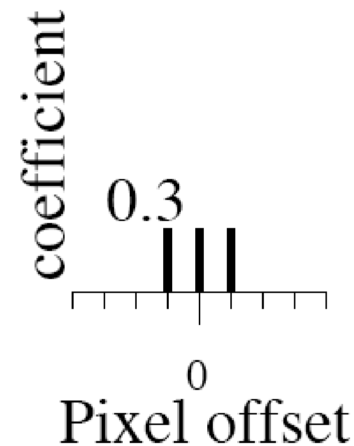
?

$I \quad \otimes \quad g \quad = f$

Blurring

$$f[m,n] = I \otimes g = \sum_k I[m-k,n]g[k]$$

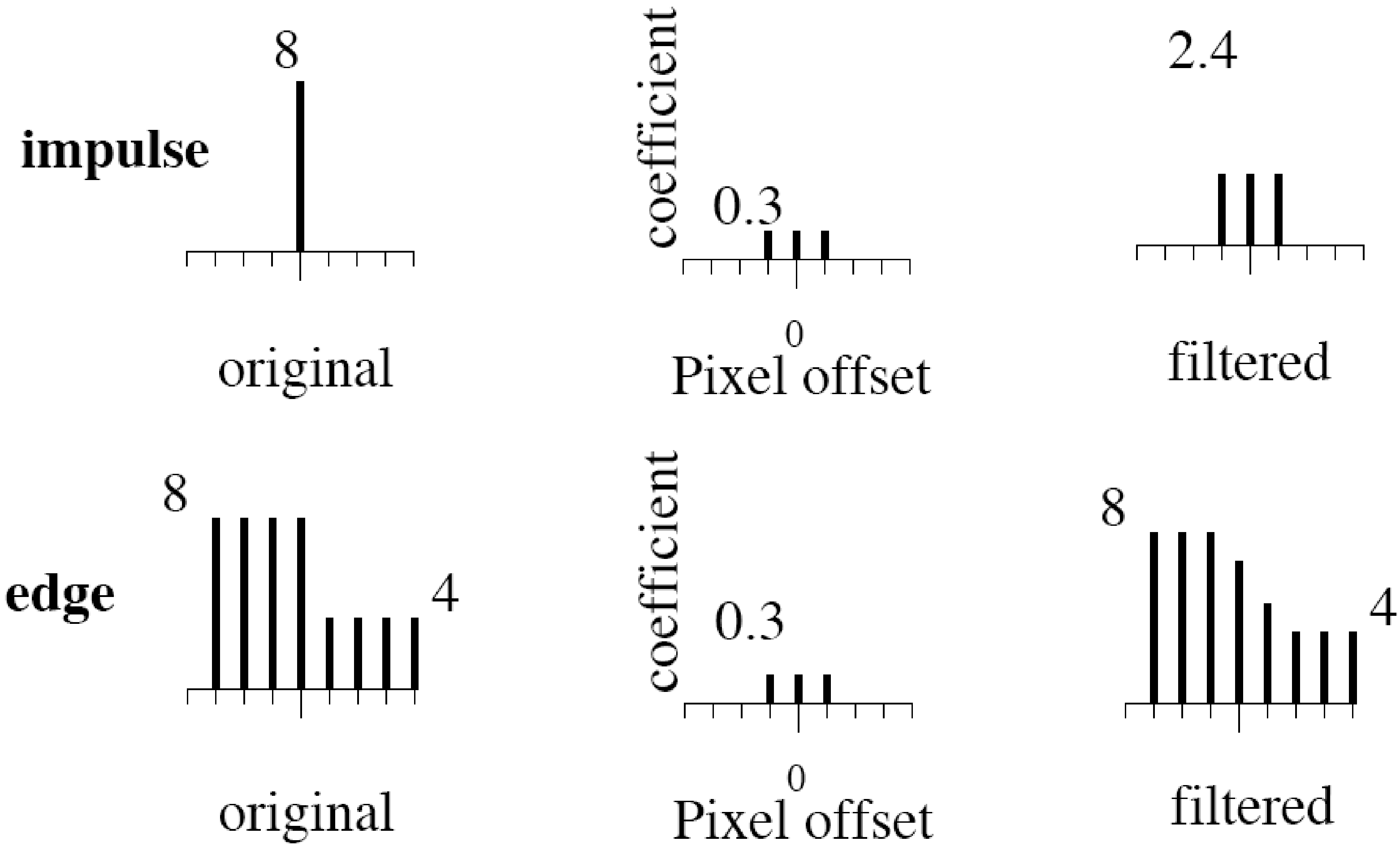
original



Blurred (filter applied in both dimensions).

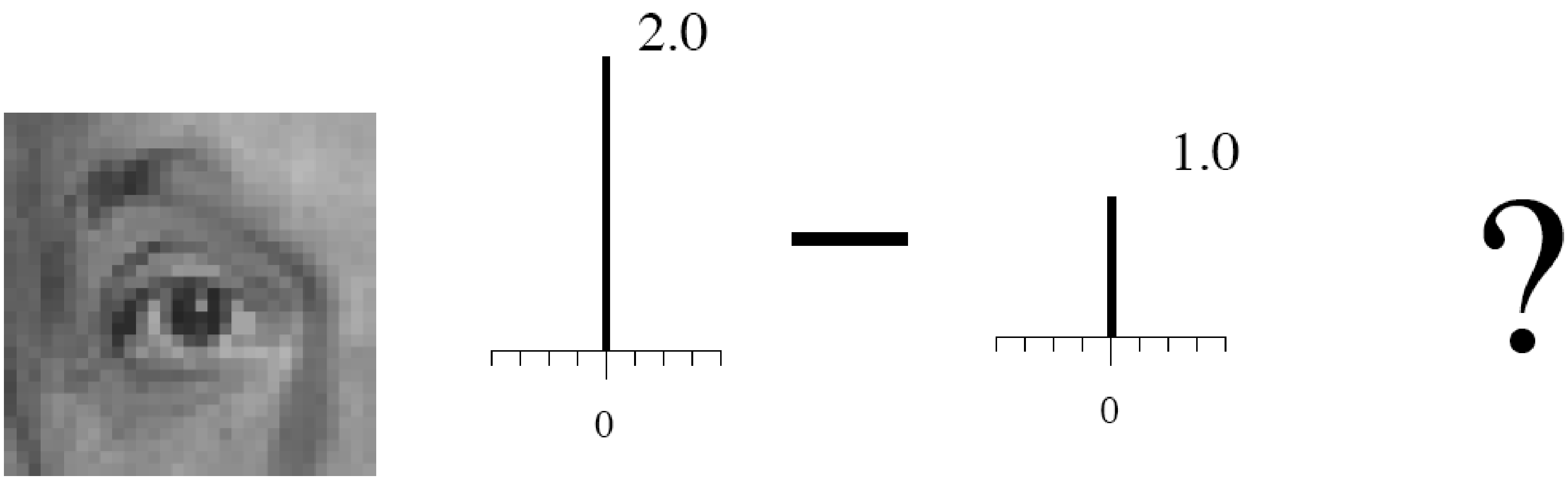
$I \qquad \otimes \qquad g$

Blurring Examples



Linear Filtering (warm-up slide)

$$f[m,n] = I \otimes g_1 - I \otimes g_2 = I \otimes (g_1 - g_2)$$

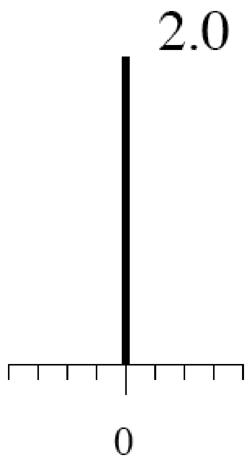


original

Linear Filtering (warm-up slide)

$$f[m,n] = I \otimes g_1 - I \otimes g_2 = I \otimes (g_1 - g_2)$$

original



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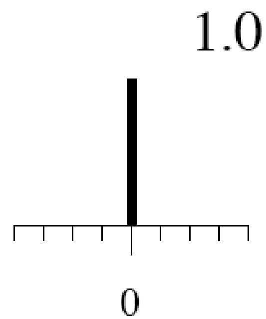
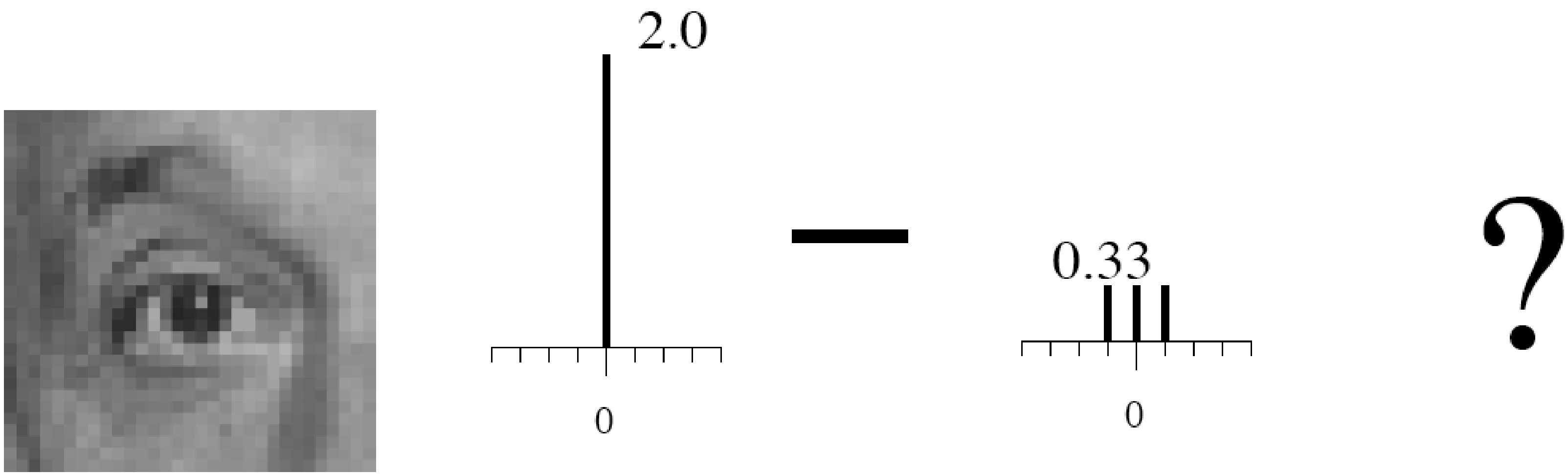


Filtered
(no change)

Linear Filtering

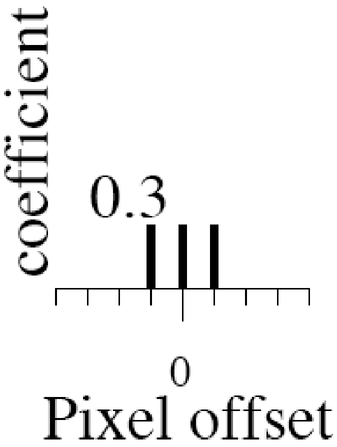
$$f[m,n] = I \otimes g_1 - I \otimes g_2 = I \otimes (g_1 - g_2)$$



original

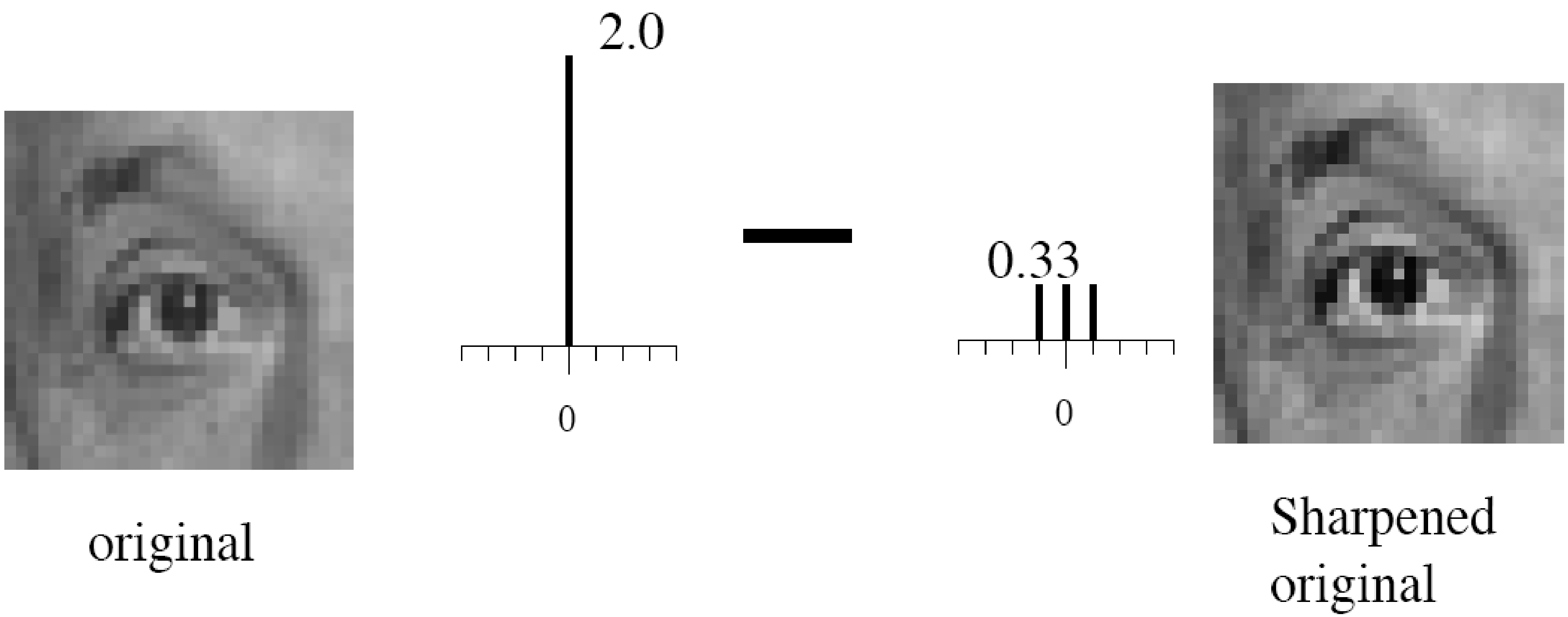
(remember blurring)

original

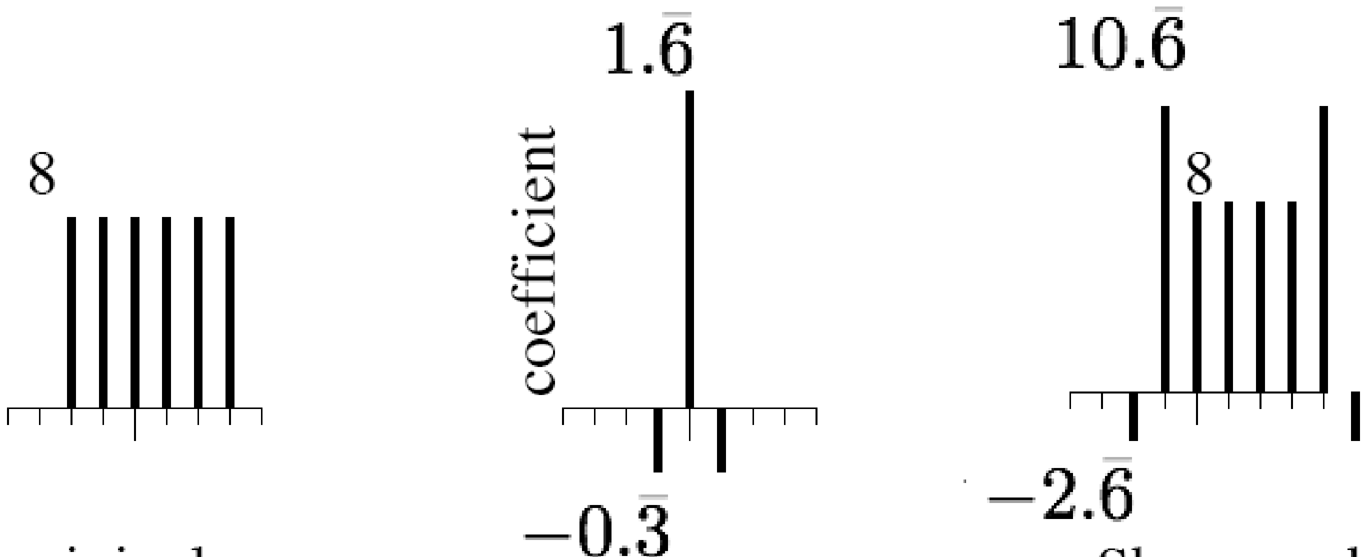


Blurred (filter applied in both dimensions).

Sharpening



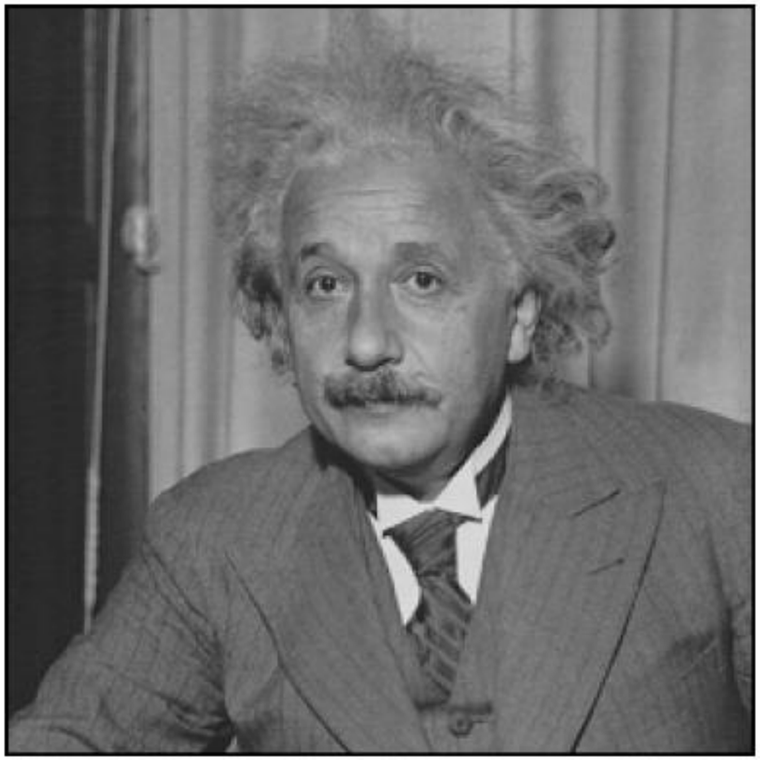
Sharpening Example



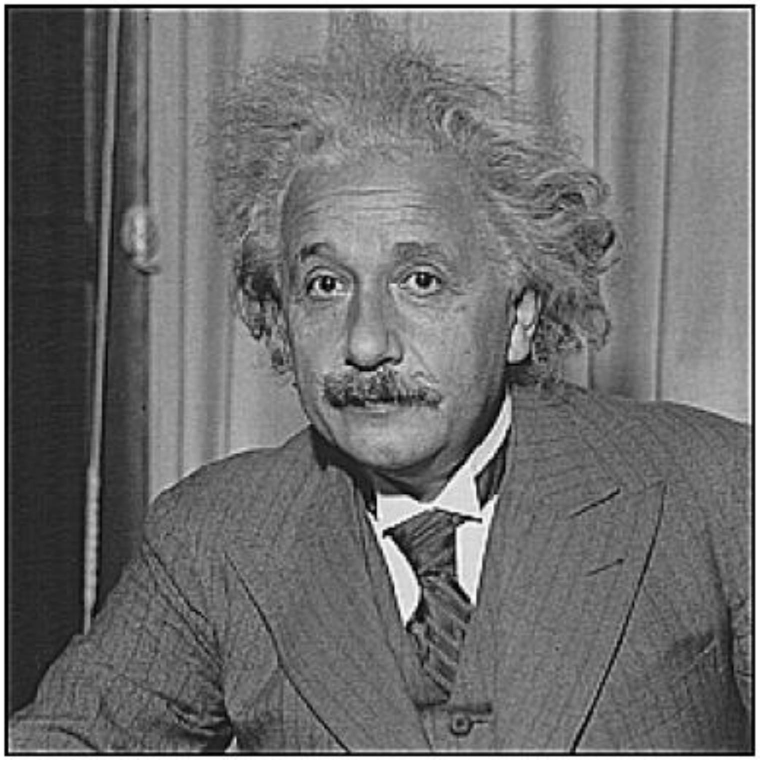
original

Sharpened
(differences are
accentuated; constant
areas are left untouched).

Sharpening



before



after

Linear Systems

- Basic Properties:
  - homogeneity $T[a X] = a T[X]$
  - additivity $T[X_1 + X_2] = T[X_1] + T[X_2]$
  - superposition $T[aX_1 + bX_2] = a T[X_1] + b T[X_2]$
  - linear systems <=> superposition

- examples:
  - matrix operations (additions, multiplication)
  - convolutions

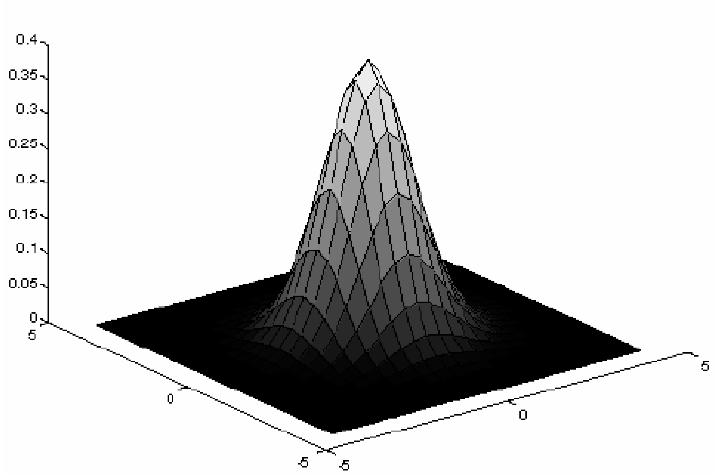
Average Filter

- Average Filter
  - replaces each pixel with an average of its neighborhood
  - Mask with positive entries that sum to 1
- if all weights are equal, it is called a BOX filter

$$\begin{array}{|c|c|c|}\hline \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \hline \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \hline \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \hline \end{array}$$

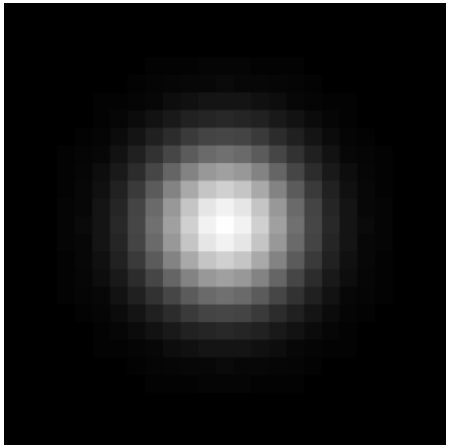
Gaussian Averaging (An Isotropic Gaussian)

- Rotationally symmetric
- Weights nearby pixels more than distant ones
  - this makes sense as 'probabilistic' inference



- the pictures show a smoothing kernel proportional to

$$g(x,y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2+y^2}{2\sigma^2}\right)$$



Smoothing with a Gaussian

- Example:

Original Image Gaussian-filtered Box-filtered

Smoothing with a Gaussian

- Another Example:

Original image

Gaussian Blur applied

Efficient Implementation

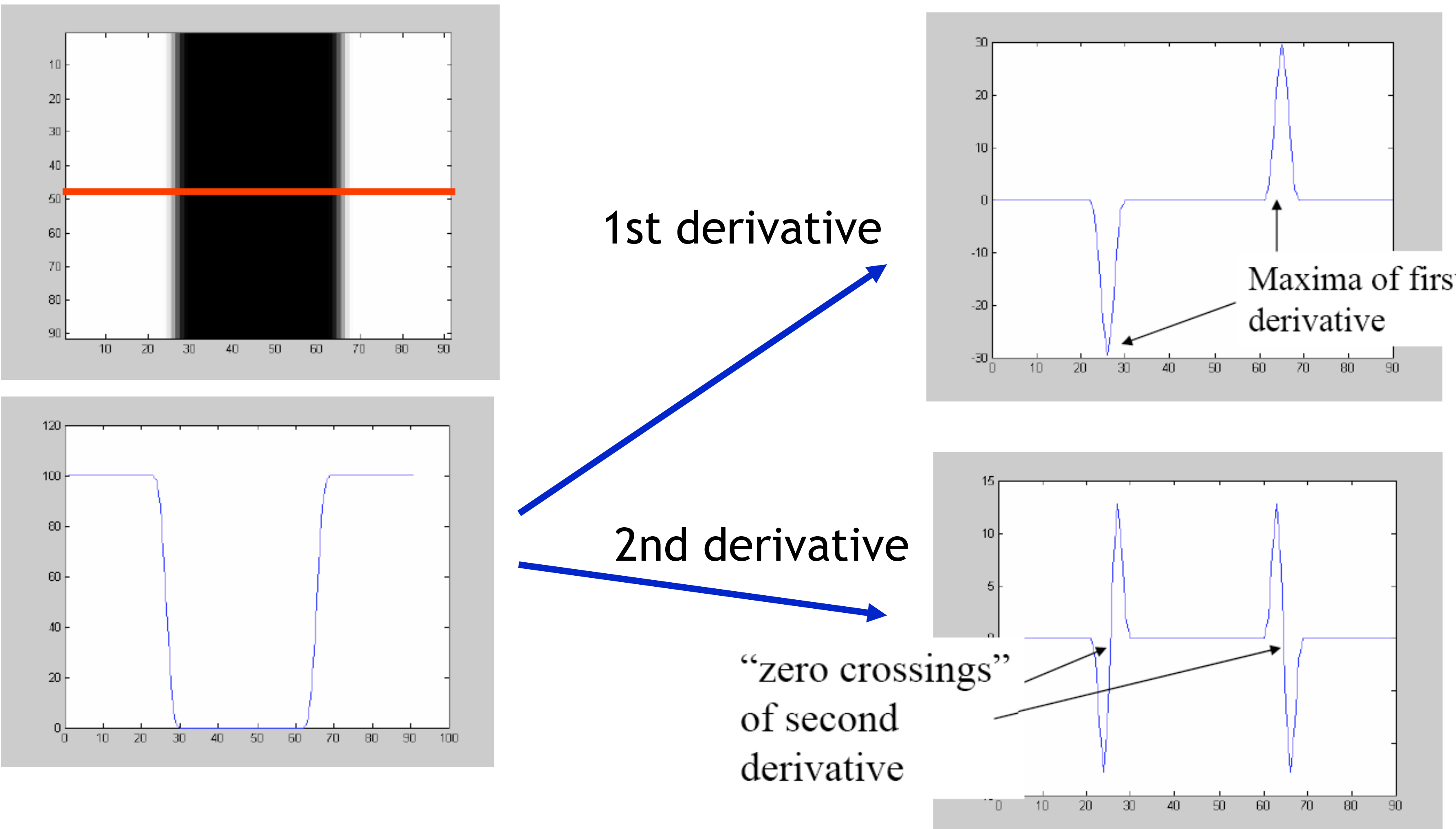
- Both, the BOX filter and the Gaussian filter are separable:
  - first convolve each row with a 1D filter
  - then convolve each column with a 1D filter

$$(f_x \otimes f_y) \otimes I = f_x \otimes (f_y \otimes I)$$

  - remember:
    - convolution is linear - associative and commutative
- Example: separable BOX filter

$$\underset{f_x \otimes f_y}{\begin{array}{|c|c|c|}\hline \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \hline \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \hline \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ \hline \end{array}} = \underset{f_x}{\begin{array}{|c|c|c|}\hline \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ \hline \end{array}} \otimes \underset{f_y}{\begin{array}{|c|}\hline \frac{1}{3} \\ \hline \frac{1}{3} \\ \hline \frac{1}{3} \\ \hline \end{array}}$$

Edges & Derivatives…



Compute Derivatives

$$\frac{d}{dx} f(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h} \approx f(x+1) - f(x)$$

- we can implement this as a linear filter:
  - direct:

-1	1

  - or symmetric:

-1	0	1

Edge-Detection

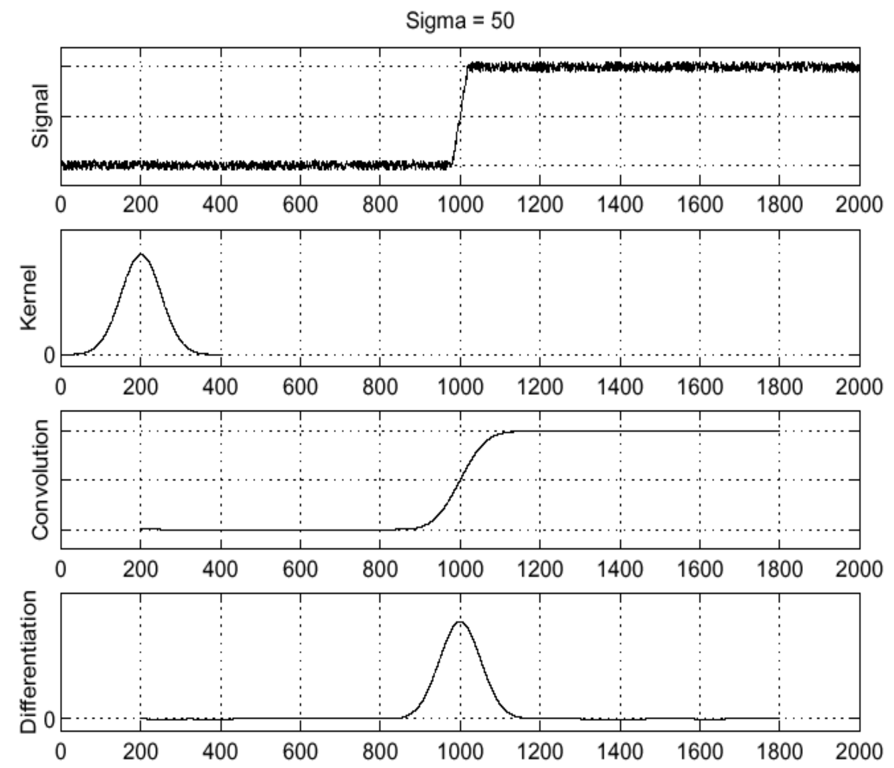
- based on 1st derivative:
    - smooth with Gaussian
    - calculate derivative
    - finds its maxima

$$f$$

$$g$$

$$g \otimes f$$

$$\frac{d}{dx}(g \otimes f)$$



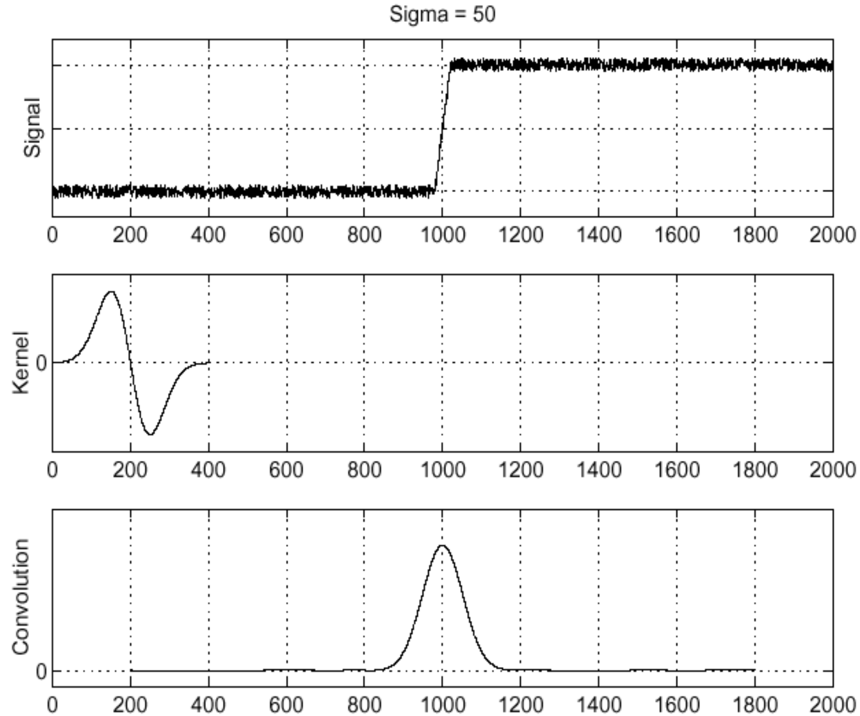
Edge-Detection

- Simplification: $$\frac{d}{dx}(g \otimes f) = \left(\frac{d}{dx}g\right) \otimes f$$
  - remember:
    derivative as well as convolution are linear operations
  - saves one operation

$$f$$

$$\frac{d}{dx}g$$

$$\left(\frac{d}{dx}g\right) \otimes f$$



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Basics of
Automatic Speech Recognition (ASR)

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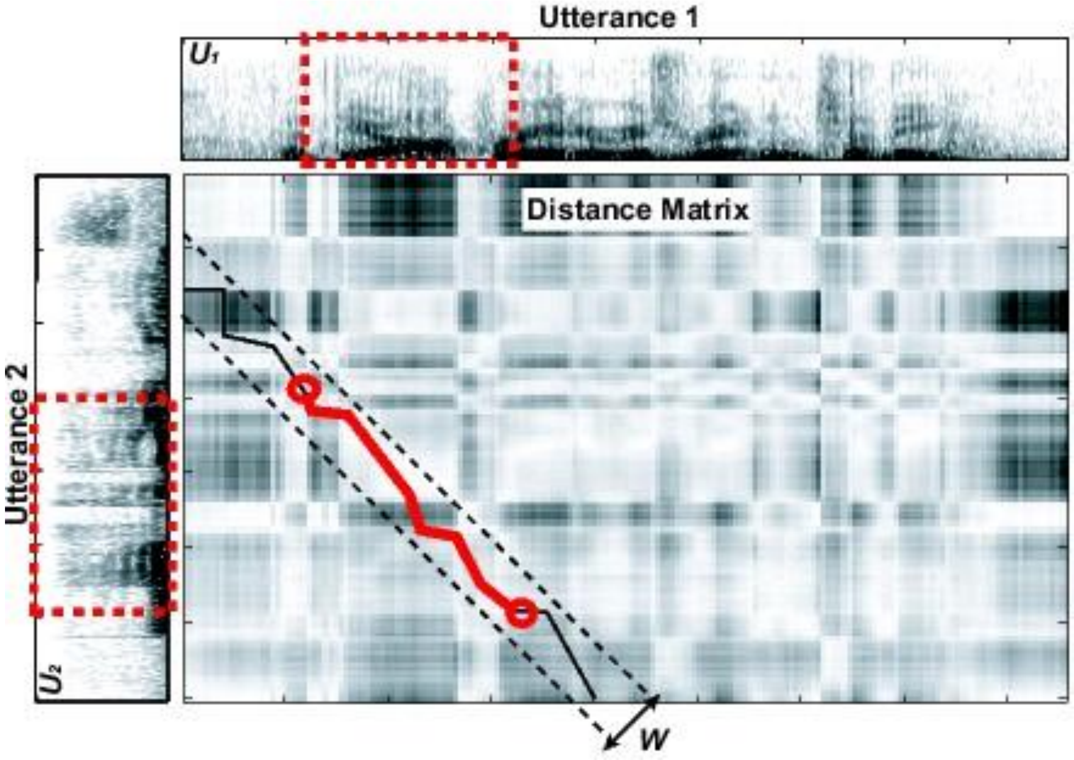
History of Automatic Speech Recognition

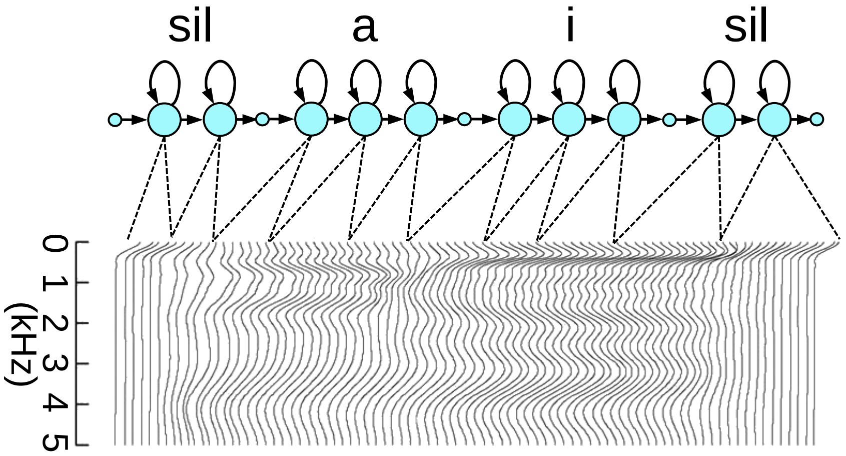
- Early 1970s: Dynamic Time Warping (DTW) to handle time variability
  - Distance measure for spectral variability



Source: http://publications.csail.mit.edu/abstracts/abstracts06/malex/seg_dtw.jpg

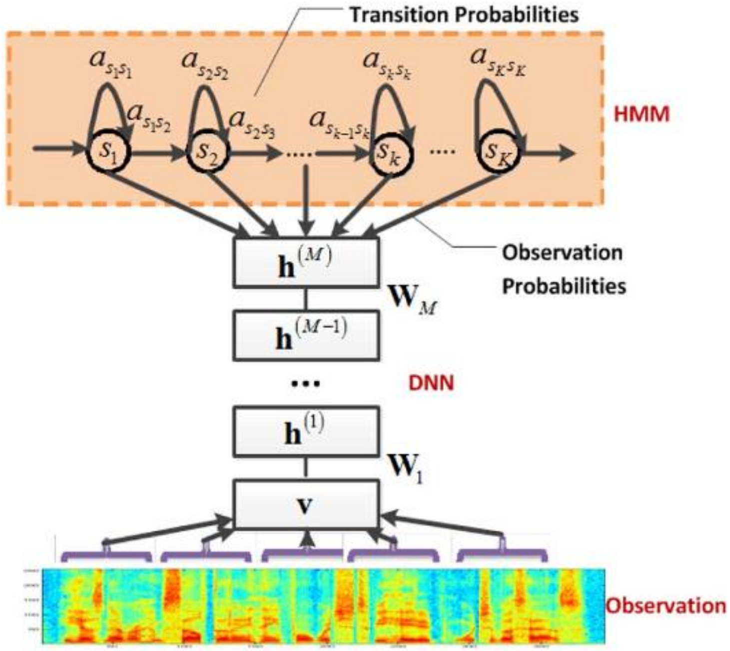
History of Automatic Speech Recognition

- Early 1970s: Dynamic Time Warping (DTW)
- Mid-Late 1970s: Hidden Markov Models (HMMs) become popular
  - statistical models of spectral variations, for discrete speech signals
- Mid 1980s: HMMs are the dominant technique for ASR



History of Automatic Speech Recognition

- Early 1970s: Dynamic Time Warping (DTW)
- Mid-Late 1970s: Hidden Markov Models (HMMs) become popular
- Mid 1980s: HMMs are the dominant technique for ASR
- 1990s: Large vocabularies and continuous dictation
- 2000s: Discriminative training (minimize word/phone error rate)
- 2010s: Deep learning significantly reduces error rate



George E. Dahl, et al. Context-Dependent Pre-Trained Deep Neural Networks for Large-Vocabulary Speech Recognition. IEEE Trans. Audio, Speech & Language Processing, 2012.

Automatic Speech Recognition

- Find the most likely sentence (word sequence) $\boldsymbol{W}$, which transcribes the speech audio $\boldsymbol{A}$:

$$\widehat{\boldsymbol{W}} = \underset{\boldsymbol{W}}{\operatorname{argmax}}\, P(\boldsymbol{W}|\boldsymbol{A}) = \underset{\boldsymbol{W}}{\operatorname{argmax}}\, P(\boldsymbol{A}|\boldsymbol{W})P(\boldsymbol{W})$$

  - Acoustic model $P(\boldsymbol{A}|\boldsymbol{W})$
  - Language model $P(\boldsymbol{W})$

- Training: optimize the acoustic and language models separately
  - Speech Corpus: speech waveform and human-annotated transcriptions
  - Language model: with extra data (prefer daily expressions corpus for spontaneous speech)

Basics of Text Analysis and Natural Language Processing (NLP)

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Word Similarity

- Task: given two words, predict how similar they are

- The Distributional Hypothesis:

You shall know a word by the company it keeps

(John Firth, 1957)

Distributional Hypothesis (J.R. Firth 1957)

- Words that occur in **similar contexts** tend to have **similar meanings**
  - “You shall know a word by the company it keeps”
  - “If A and B have almost identical environments ”

- Words which are **synonyms** tend to occur in the **similar context**

Intuition of distributional word similarity

- Suppose I asked you what is **tesgüino**?

A bottle of **tesgüino** is on the table
Everybody likes **tesgüino**
Tesgüino makes you drunk

- From context words, humans can guess **tesgüino** an alcoholic beverage like beer
- Intuition for the algorithm:
  - Two words are similar if they have **similar** word **contexts**

🌟 Vector semantics

- **Goal**: Learning **representations** (embeddings) of the meaning of words, directly from their **distributions** in text
- Important for NLP applications that make use of meaning
  - Question Answering, Summarization, Detecting paraphrases or plagiarism and dialogue

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Term-document matrix

- Count of word w in a document d:
  - Each document in a count vector in $\mathbb{N}^{V}$

Document

	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

Word / Term

Word-word matrix

- Instead of an entire document, use smaller contexts
  - Paragraph
  - Window of +-4 words

- Word is now defined by counts of context words

	aardvark	...	computer	data	result	pie	sugar	...
cherry	0	...	2	8	9	442	25	
strawberry	0	...	0	0	1	60	19	
digital	0	...	1670	1683	85	5	4	
information	0	...	3325	3982	378	5	13	

TF-IDF: Weighting terms in the vector

- Not all words are equally important
  - Some words just co-occur frequently with many different words (e.g. the, they, it)
- **Term Frequency:** Words that occur nearby frequently (maybe *pie* nearby *cherry*) are more important.
- **Inverse Document Frequency:** Words that are too frequent may be unimportant (e.g. *the*, *it, he*, she).

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Measuring similarity

- We have words *w* and *v*
- How do we measure their similarity?

- **Dot product** or **inner product** from linear algebra

$$dot\text{-}product(\vec{v},\vec{w}) = \vec{v}\cdot\vec{w} = \sum_{i=1}^{N} v_i w_i$$

  - High when two vectors have large values in same dimensions
  - Low (actually 0) for **orthogonal vectors**

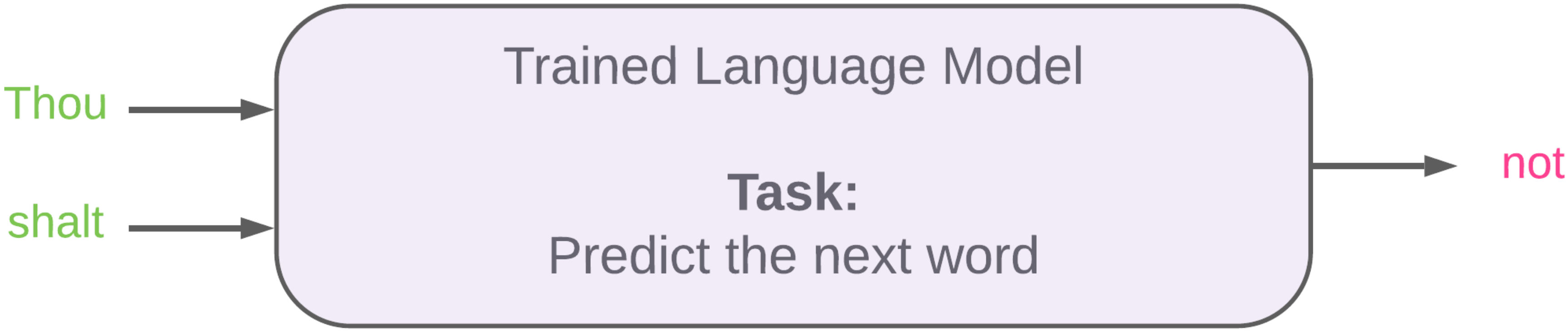
Review: Language Modeling

- Next-word prediction task

input # 1 input # 2 output

Thou shalt ______

Review: Language Modeling



Review: Language Modeling

Thou shalt not make a machine in the likeness of a human mind

Sliding window across text

thou	shalt	not	make	a	machine	....

Dataset

input 1	input 2	output
thou	shalt	not

Thou shalt not make a machine in the likeness of a human mind

Sliding window across text

thou	shalt	not	make	a	machine	....
thou	shalt	not	make	a	machine	....

Dataset

input 1	input 2	output
thou	shalt	not
shalt	not	make

Review: Language Modeling

Thou shalt not $\boxed{\text{make a machine}}$ in the likeness of a human mind

Sliding window across text

thou	shalt	not	make	a	machine	....
thou	shalt	not	make	a	machine	....
thou	shalt	not	make	a	machine	....
thou	shalt	not	make	a	machine	....

Dataset

input 1	input 2	output
thou	shalt	not
shalt	not	make
not	make	a
make	a	machine

Thank you

Acknowledges: some slides and material from Bernt Schiele, Mario Fritz, Michael Black, Bill Freeman, Fei-Fei, Justin Johnson, Serena Yeung, Yining Chen, Anand Avati, Andrew Ng

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