Machine Learning

Different Data Formats

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Outline

Data formats

Text

Images

Intro

So far:

- Supervised and non-supervised ML.
- Classification, regression, clustering, dimensionality reduction.
- Always assuming we already got numeric data: vectors.

What about other types of data? E.g.,

- Text,
- Images or video,
- Audio,
- Radio frequencies,
- Etc.

Data must be converted into a numeric descriptor, i.e., vector.

Different formats

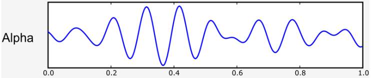
Most types of data can be understood as either:

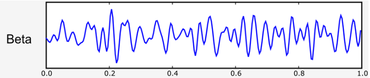
Static data

Vectors, as we already know.

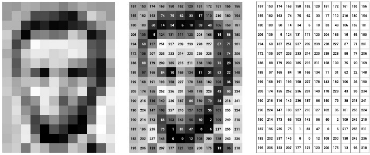
Sequential data

Text, sound, voltage, etc.





Spatial data

Images. 

Or a combination of both, e.g., video.

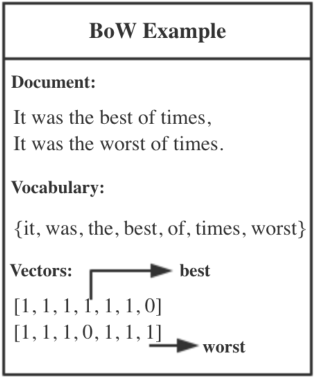
Exploit other formats

Design filters that extract relevant statistics, create vectors.

Outline

BoW

Bag-of-words (BoW): vector that counts frequency of words.



Idea: documents of similar topic, have similar word distribution.

Considerations

- Put all characters in lowercase.
- Remove punctuation and special characters.
- Remove numbers.
- Remove stopwords (articles, prepositions, etc).
- Use lematization or stemming.

TD-IDF

Term frequency - inverse document frequency (tf-idf): used for weighting each term with a inverse frequency with respect to documents: terms appearing in all documents are of low relevance.

$$w_{x,y} = tf_{x,y} \times \log\left(\frac{N}{df_x}\right)$$

TF-IDF

Term x within document y

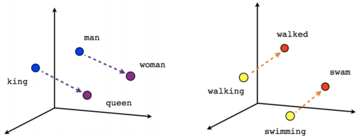
$tf_{x,y}$ = frequency of x in y

df_x = number of documents containing x

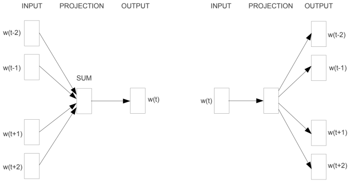
N = total number of documents

Embeddings

Starting from one-hot encoding vectors, find rich dense representation that capture semantic context of words.



Male-Female Verb tense

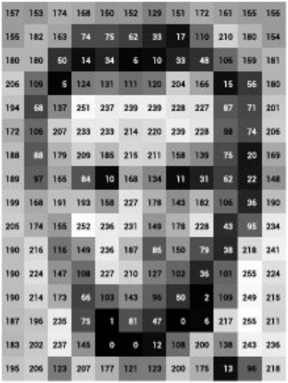


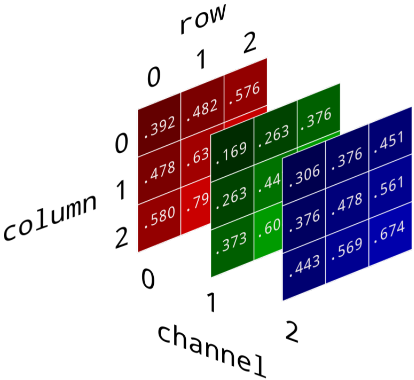
CBOW Skip-gram

Outline

Image formation

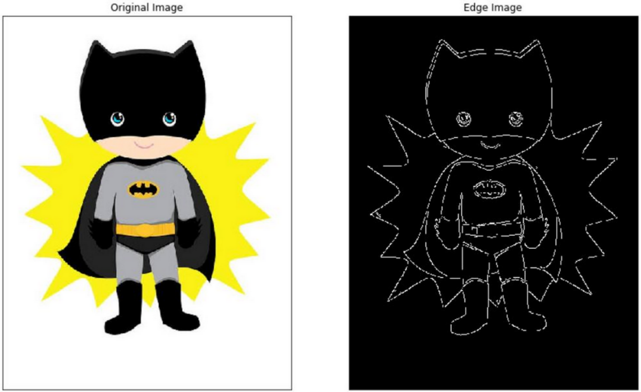
Each pixel indicates a relative amount of light captured by a sensor.



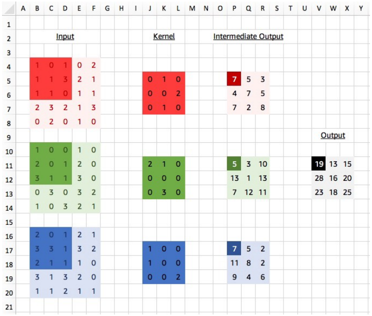


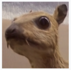
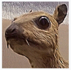
Derivatives in 2D

Edge detector:



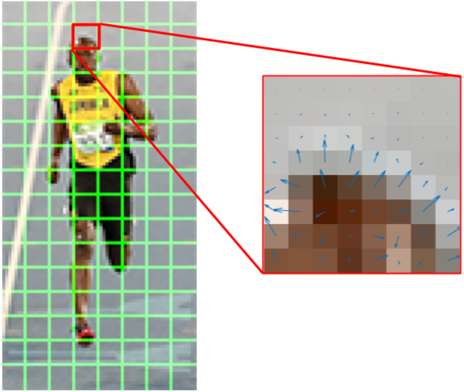
Convolution



Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur 3 × 3 (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

HOG

Histogram-of-Oriented-Gradients.



2	3	4	4	3	4	2	2
5	11	17	13	7	9	3	4
11	21	23	27	22	17	4	6
23	99	165	135	85	32	26	2
91	155	133	136	144	152	57	28
98	196	76	38	26	60	170	51
165	60	60	27	77	85	43	136
71	13	34	23	108	27	48	110

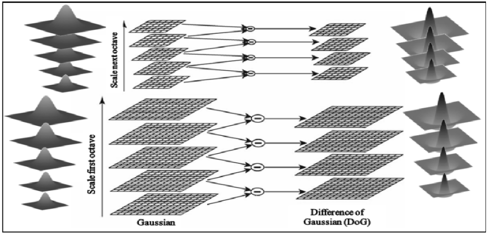
Gradient Magnitude

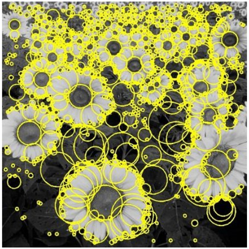
80	36	5	10	0	64	90	73
37	9	9	179	78	27	169	166
87	136	173	39	102	163	152	176
76	13	1	168	159	22	125	143
120	70	14	150	145	144	145	143
58	86	119	98	100	101	133	113
30	65	157	75	78	165	145	124
11	170	91	4	110	17	133	110

Gradient Direction

Local image descriptor

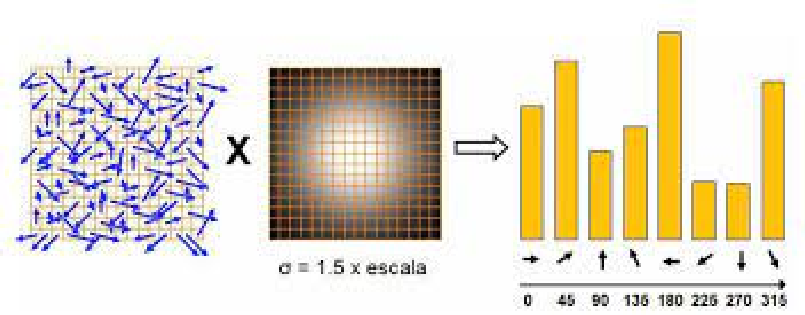
Detect points of interest (PoI): corners of blobs.





SIFT

Scale-Invariant Feature Transform



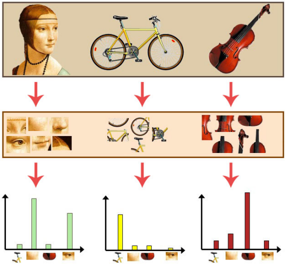
Each local descriptor is a 128-D vector. There are as many local descriptors as PoI's were detected.

BoVW

Count the frequency of *visual words* (types of local descriptors).

Descriptors are vectors in $\mathbb{R}^N$, let's map them to $\mathbb{Z}$.

1. Grab a set of local descriptors.
2. Use a clustering algorithm to group them in D clusters.
3. Label each descriptor with the index of its cluster.
4. Create a D-dimensional vector of visual words.



Q&A

Thank you!

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