# Machine Learning and Face Recognition

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Department of Chemistry
Aarhus University

Machine Learning Study Group, November 13th 2017

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# Outline



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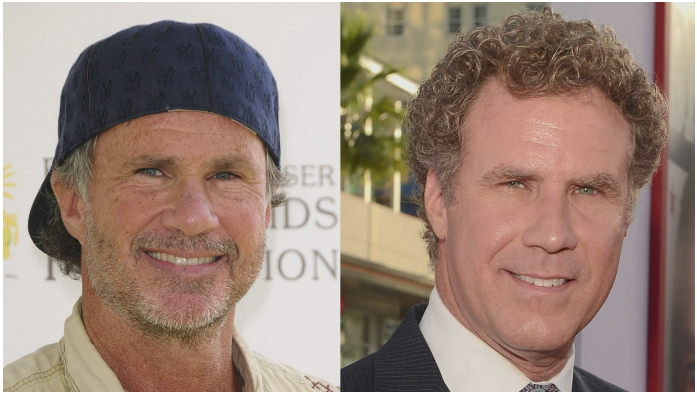
# Telling Chad Smith and Will Ferrell apart



Based on Adam Geitgey's Machine Learning blog (see *Further Reading*).

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# Courtesy of our Evil Overlords

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FaceNet (Schroff et al., 2015)

DeepFace (Taigman et al., 2014)

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# Face Recognition Is a Complex Process

1. Face detection: e.g. histogram of oriented gradients (HOG), convolutional neural networks (CNN).
2. Input preparation: e.g. linear transformation or 3D-warping.
3. *'Embedding'* from (conventional/fully-connected) neural network (NN).
4. Recognition using simple classification algorithm: e.g. support vector machines (SVM).


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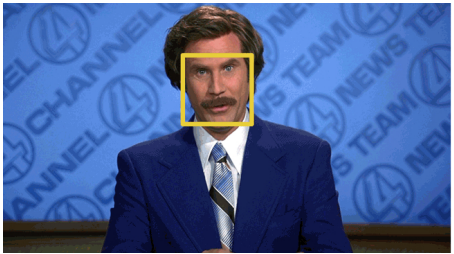

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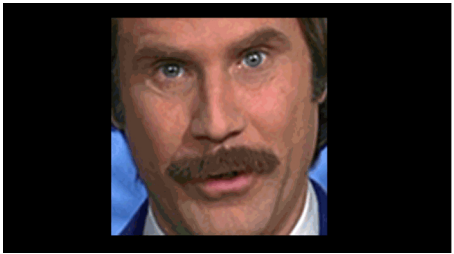

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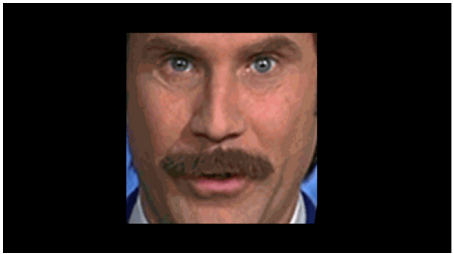

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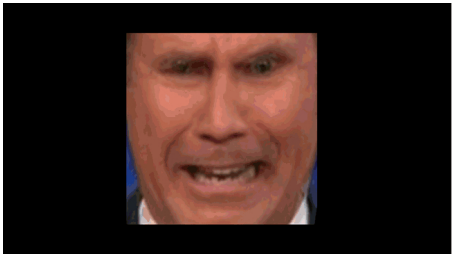

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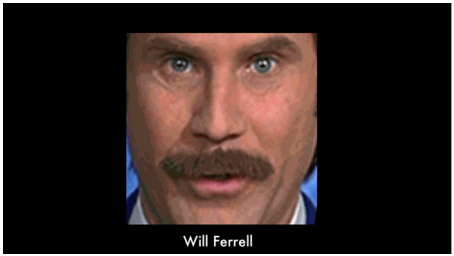


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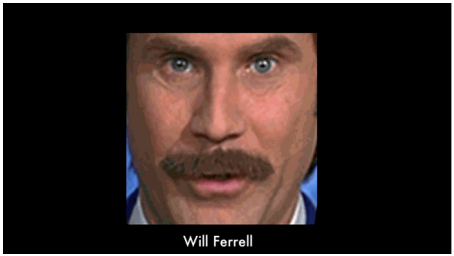


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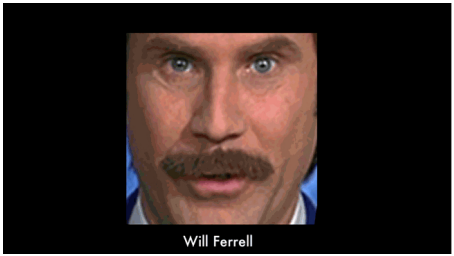


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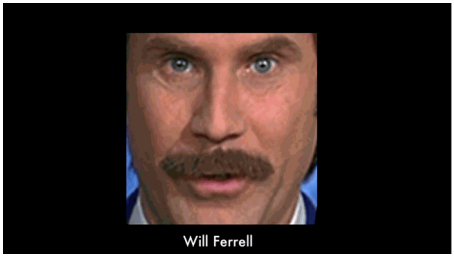


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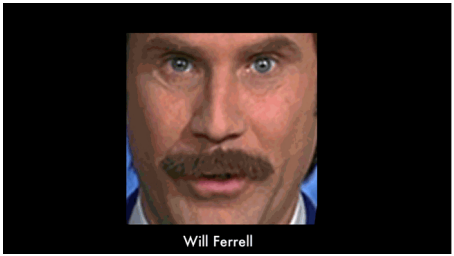


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# Step 1, Face Detection: Histogram of Oriented Gradients (HOG)

- B/W: faces depend on shape/contours, not colors.
- Dealing with brightness differences: pixel-wise gradients (HOG). (Now superseded by CNN?)
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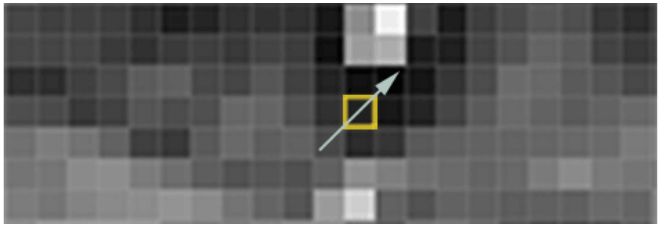

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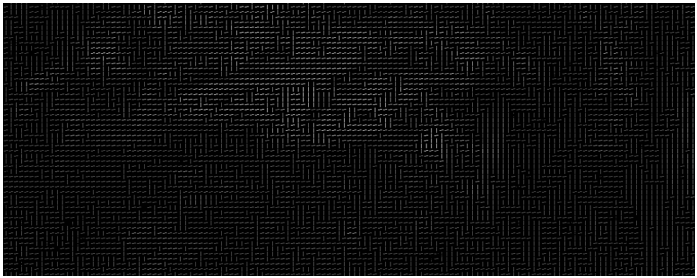

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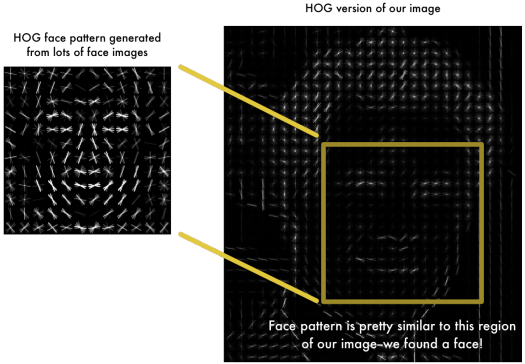


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# Step 2, Input Preparation: Facial Landmarks

Kazemi, Sullivan (2014)

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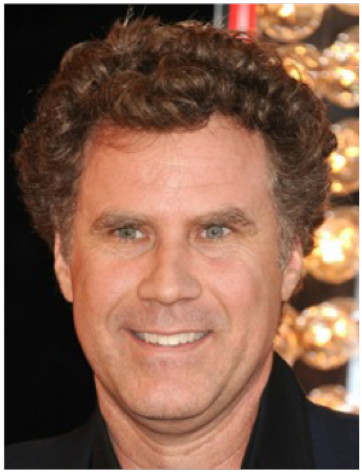

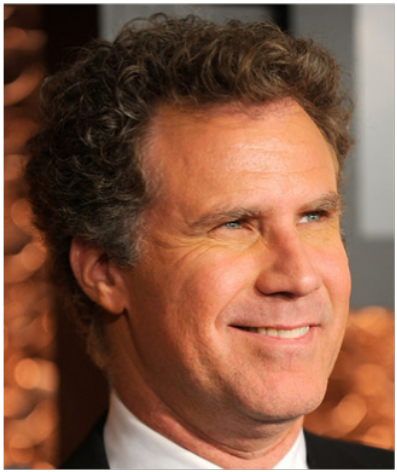

Dealing with different orientations?

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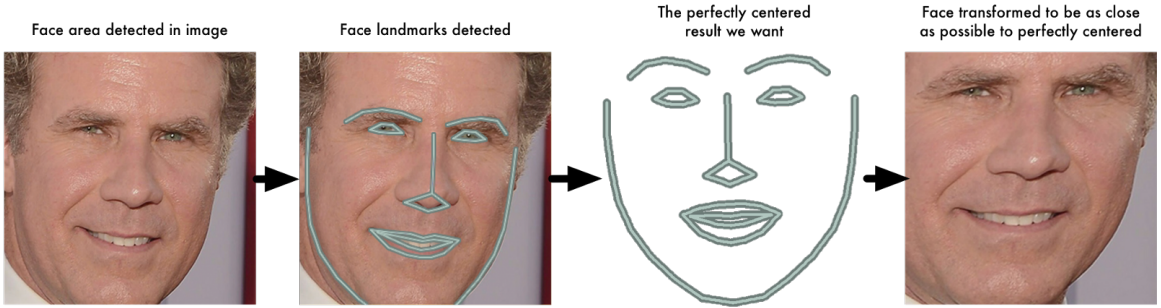


Linear transformation (preserves parallel lines) (Google's FaceNet?)

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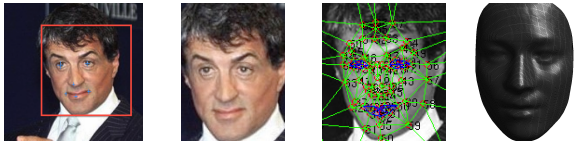

(a) (b) (c) (d)

(e) (f) (g) (h)

Facebook's DeepFace: 3D-warp

# Step 2, Input Preparation: Facial Landmarks

- Importance: feed suitable input to NN.
- Trade-off: simpler input vs. NN training time.
- Perspective: Behler paper, interatomic distances, symmetrization.

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# Step 3, Embedding from Neural Network: Google's Triplet Loss Function

- NN: input (pixels, HOG) $\rightarrow$ output (what?)
- Output: 'embedding' = parameter vector ($\in \mathcal{R}^{128}$ for Google's FaceNet)
- If humanly engineered: e.g. eye separation, nose width, etc.
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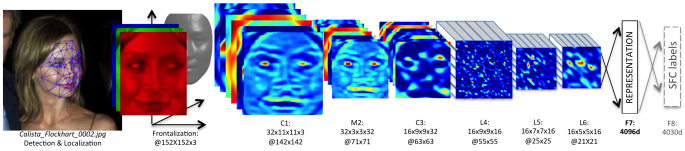

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Input Image

128 Measurements Generated from Image

| | | | |
|---|---|---|---|
| 0.097496084868908 | 0.045223236083984 | -0.1281466782093 | 0.032084941864014 |
| 0.12529824674129 | 0.060309179127216 | 0.17521631717682 | 0.020976085215807 |
| 0.030809439718723 | -0.019814777253139 | 0.10801389068365 | -0.000521637278451189 |
| 0.036050599068403 | 0.065554238855839 | 0.073130600015444 | -0.13189511100111 |
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| -0.0066401711665094 | 0.036753039169292 | -0.15958009660244 | 0.043374512344599 |
| -0.14131525188882 | 0.14114324748516 | -0.031351584941149 | -0.053436127700701 |
| -0.048540540039539 | -0.061901587992907 | -0.15042643249035 | 0.078198105096817 |
| -0.12567175924778 | -0.10568545013666 | -0.12728653848171 | -0.076289616525173 |
| -0.061418771743774 | -0.074287034571171 | -0.065365232572256 | 0.12369407318058 |
| 0.046741496771574 | 0.006176188122481 | 0.14746543765068 | 0.056418422609568 |
| -0.12113650143147 | -0.21055991947651 | 0.004109122790396 | 0.089727647602558 |
| 0.061606746166945 | 0.11345765739679 | 0.021352224051952 | -0.008584329858223 |
| 0.061988940702915 | 0.19372203946114 | -0.086726233363152 | -0.022388197481632 |
| 0.10904195904732 | 0.084853030741215 | 0.094635948353878 | 0.020696049556136 |
| -0.019414527341723 | 0.006481129676106 | 0.21180312335491 | -0.050584398210049 |
| 0.15245945751667 | -0.16582328081131 | -0.035577941885915 | -0.072376452386379 |
| -0.12216668576002 | -0.0072777755558491 | -0.036901291459799 | -0.034365277737379 |
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| -0.021407851949334 | 0.14841195940971 | 0.078333757817745 | -0.17898085113387 |
| -0.018298890441656 | 0.049525424838066 | 0.13227833807468 | -0.072600327432156 |
| -0.011014151386917 | -0.051016297191381 | -0.14132921397686 | 0.005051190827528 |
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| 0.058139257133007 | 0.004863874055452 | -0.039491076022387 | -0.043765489012003 |
| -0.024210374802351 | -0.11443792283535 | 0.071997955441475 | -0.012062266460602 |
| -0.057223934680223 | 0.014983869667351 | 0.052281547337777 | 0.012774495407939 |
| 0.023535015061498 | -0.081752359867096 | -0.031709920614958 | 0.069833360612392 |
| -0.009803973383324 | 0.037022035568953 | 0.11009479314089 | 0.11638788878918 |
| 0.020220354199409 | 0.12788131833076 | 0.18632389605045 | -0.015367929216059 |
| 0.004033768083902 | -0.094398014247417 | -0.11768248677254 | 0.10281457751989 |
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| 0.004033768083902 | -0.094398014247417 | -0.11768248677254 | 0.10281457751989 |
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128 Measurements Generated from Image

| | | | |
|---|---|---|---|
| 0.097496084868908 | 0.045223236083984 | -0.1281466782093 | 0.032084941864014 |
| 0.12529824674129 | 0.060309179127216 | 0.17521631717682 | 0.020976085215807 |
| 0.030809439718723 | -0.019814777253139 | 0.10801389068365 | -0.00052163278451189 |
| 0.036505099068403 | 0.065554238855839 | 0.073130600015444 | -0.13189511100111 |
| -0.097486883401871 | 0.1226262897253 | -0.029626874253154 | -0.0059557510539889 |
| -0.0066401711665094 | 0.036753039169292 | -0.15958009660244 | 0.043374512344599 |
| -0.14131525188882 | 0.14114324748516 | -0.031351584941149 | -0.053436127700701 |
| -0.048540540039539 | -0.061901587992907 | -0.15042643249035 | 0.078198105096817 |
| -0.12567175924778 | -0.10568545013666 | -0.12728653848171 | -0.076289616525173 |
| -0.061418771743774 | -0.074287034571171 | -0.065365232572256 | 0.12369407318058 |
| 0.046741496771574 | 0.006176188122481 | 0.14746543765068 | 0.056418422609568 |
| -0.12113650143147 | -0.21055991947651 | 0.0041091227903962 | 0.089727647602558 |
| 0.061606746166945 | 0.11345765739679 | 0.021552224051952 | -0.0085843298584223 |
| 0.061988940702915 | 0.19372203946114 | -0.086726233363152 | -0.022388197481632 |
| 0.10904195904732 | 0.084853030741215 | 0.09463594853878 | 0.020696049556136 |
| -0.019414527341723 | 0.006481129676106 | 0.21180312335491 | -0.050584398210049 |
| 0.15245945751667 | -0.16582328081131 | -0.035577941685915 | -0.072376452386379 |
| -0.12216668576002 | -0.0072777755558491 | -0.036901291459799 | -0.034365277737379 |
| 0.083934605121613 | -0.059730969369411 | -0.070026844739914 | -0.045013956725597 |
| 0.087945111065905 | 0.11478432267904 | -0.089621491730213 | -0.013955107890069 |
| -0.021407851949334 | 0.14841195940971 | 0.078333757817745 | -0.17898085113387 |
| -0.018298890441656 | 0.049525424838066 | 0.13227833807468 | -0.072600327432156 |
| -0.011014151386917 | -0.051016297191381 | -0.14132921397686 | 0.005051190827528 |
| 0.009367933496832 | -0.062812767922878 | -0.13407498598099 | -0.014829395338893 |
| 0.058139257133007 | 0.0048638740554452 | -0.039491076022387 | -0.043765489012003 |
| -0.024210374802351 | -0.11443792283535 | 0.071997955441475 | -0.012062266460602 |
| -0.057223934680223 | 0.014983869667351 | 0.052281547377 | 0.012774495407939 |
| 0.023535015061498 | -0.081752359867096 | -0.031709920614958 | 0.069833360612392 |
| -0.0098039731383324 | 0.037022035568953 | 0.11009479314089 | 0.11638788878918 |
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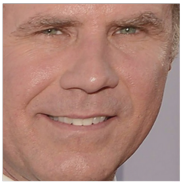

128 Measurements Generated from Image

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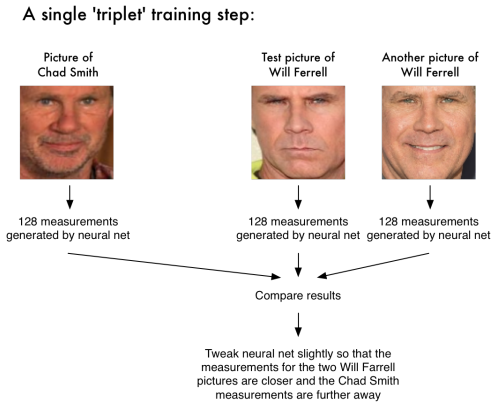


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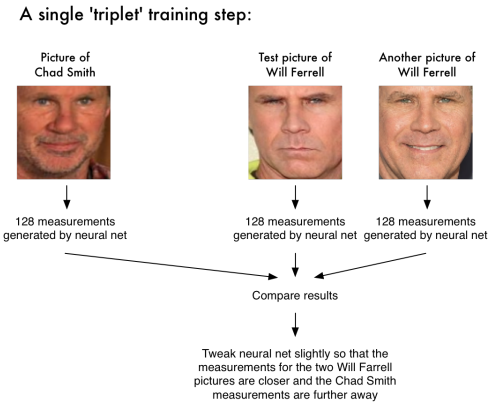


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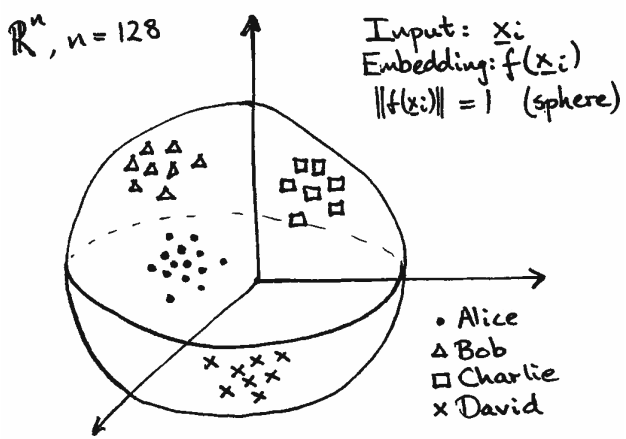
# Step 4, Recognition: Classification algorithm

- The NN embeddings:
  - alike for identical persons.
  - distant for different persons.
- Train a ML classification algorithm (such as SVM) with known faces.
- Feed image, generate embedding, classify as known person.

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# Outline



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# Convolution Essentials

- In math: $s(t) = \int x(a)w(t-a)da$
  where $w$: weight, $x$: signal
- Discrete: $s(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a)$
- 2D:

$$S(i,j) = \sum_{m,n} I(i+m, j+n)K(m,n)$$

where $I$: image, $K$: kernel [1]

[1] Actually, this formula is called *cross-correlation* while *convolution* has terms like $I(i-m, j-n)K(m,n)$, i.e. the kernel is *flipped* relative to the image. *Convolution* is handier for math proofs, *cross-correlation* is (maybe?) more intuitive to implement and interpret, and in the end the NN doesn't care; it just optimizes the weights in either case. The terms are sometimes used interchangeably by the community. See Goodfellow, ch. 9.

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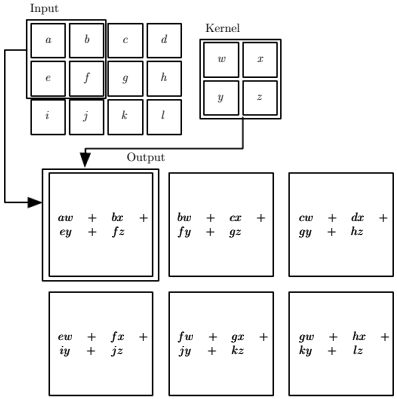


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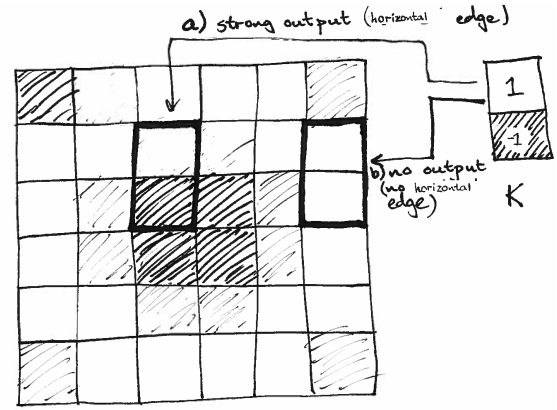
# Convolution as "filter"/feature detector

- Convolution extracts features located *anywhere*.
- Edge detection (compare with HOG).
- Humanly engineered: we might look for eye contours, etc.
- ML: just train a CNN to figure out the best kernel(s), i.e. best features to look for.

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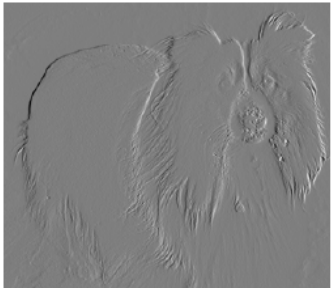

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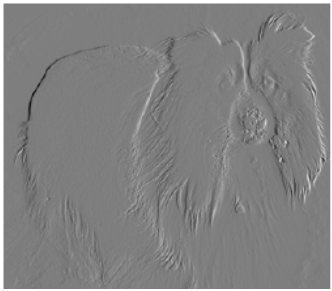

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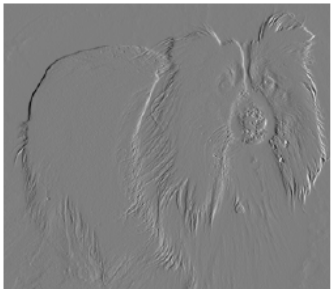

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# Pooling

- A "summary" of statistics of the NN layer output (often used with CNN).
- E.g.: max pooling; just select the max. element in area.
- Robustness towards small, insignificant variations.
- Data reduction (using strides).

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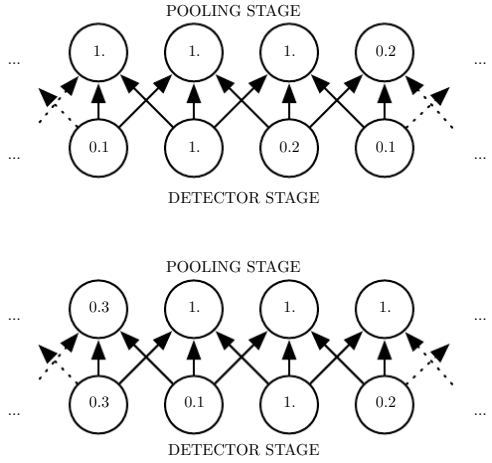


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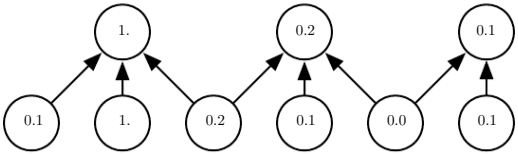


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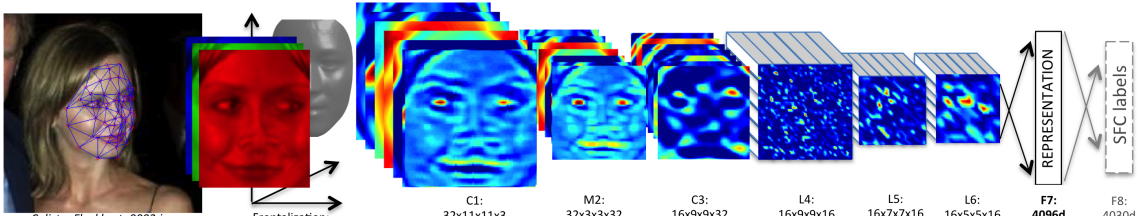
# CNN and pooling: Facebook's DeepFace revisited




[2]"A 3D-aligned 3-channels (RGB) face image of size 152 by 152 pixels is given to a convolutional layer (C1) with 32 filters of size 11x11x3 (we denote this by 32x11x11x3@152x152). The resulting 32 feature maps are then fed to a max-pooling layer (M2) which takes the max over 3x3 spatial neighborhoods with a stride of 2, separately for each channel. This is followed by another convolutional layer (C3) that has 16 filters of size 9x9x16. The purpose of these three layers is to extract low-level features, like simple edges and texture. [...] The subsequent layers (L4, L5 and L6) are instead locally connected, like a convolutional layer they apply a filter bank, but every location in the feature map learns a different set of filters." (MBH: i.e. they extract features specific to that region of the face.) "[...] Finally, the top two layers (F7 and F8) are fully connected: each output unit is connected to all inputs. These layers are able to capture correlations between features captured in distant parts of the face images, e.g., position and shape of eyes and position and shape of mouth."

# Outline



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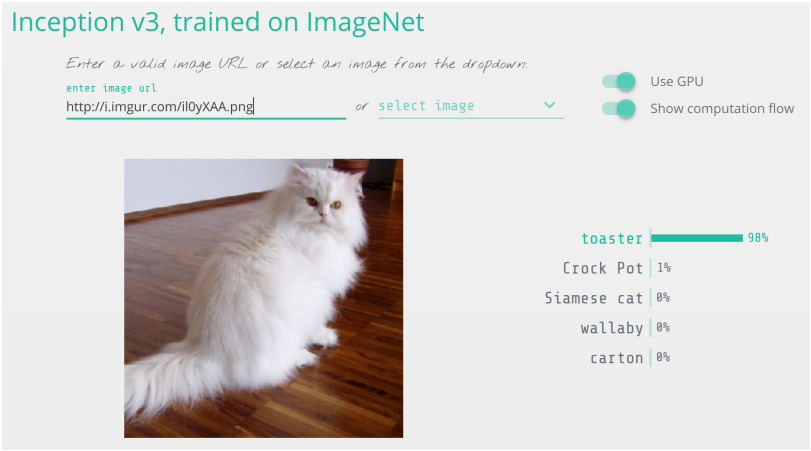
# How to Hack a Neural Network

Adam Geitgey's block, part 8: Optimize the image, not the NN weights.

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# Summary/perspectives

- Importance of NN input.
- Convolutional NN/pooling for feature detection.
- High quality, well documented, open source C++ library (dlib) for ML.

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# Further Reading and Resources I

- Adam Geitgey. *Machine Learning is Fun! Part 4: Modern Face Recognition with Deep Learning* (2016). (Comment: blog that much of this presentation was based upon – the other parts contain good, digestable introductions to many ML aspects as well.)
- Florian Schroff, Dmitry Kalenichenko, James Philbin. *FaceNet: A Unified Embedding for Face Recognition and Clustering* (2015). (Comment: Google's face recognition technique.)
- Yaniv Taigman, Ming Yang, Marc'Aurelio Ranzato, Lior Wolf. *DeepFace: Closing the Gap to Human-Level Performance in Face Verification* (2014). (Comment: Facebook's face recognition technique.)
- Navneet Dalal, Bill Triggs. *Histograms of Oriented Gradients for Human Detection* (2005).
- Vahid Kazemi, Josephine Sullivan. *One Millisecond Face Alignment with an Ensemble of Regression Trees (2014).* (Comment: About aligning faces using 'facial landmarks'.)

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# Further Reading and Resources II

- Ian Goodfellow, Yoshua Bengio, Aaron Courville. *Deep Learning (2016).* (Comment: All the essentials, by three of the authorities (from what I understood) in the field. HTML version on site, PDF-version here.)
- *dlib C++ library.* (Comment: (in their own words) high quality, well documented, open source machine learning toolkit. I managed to install it and run a face detection script using it on my Mac more or less out of the box.)

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