

Deep Learning:
Searching for Images

Emily Fox & Carlos Guestrin
Machine Learning Specialization
University of Washington

©2015 Emily Fox & Carlos Guestrin

Visual product recommender

I want to buy new shoes, but…




Too many options online…




©2015 Emily Fox & Carlos Guestrin

Text search doesn't help…





"Dress shoes"





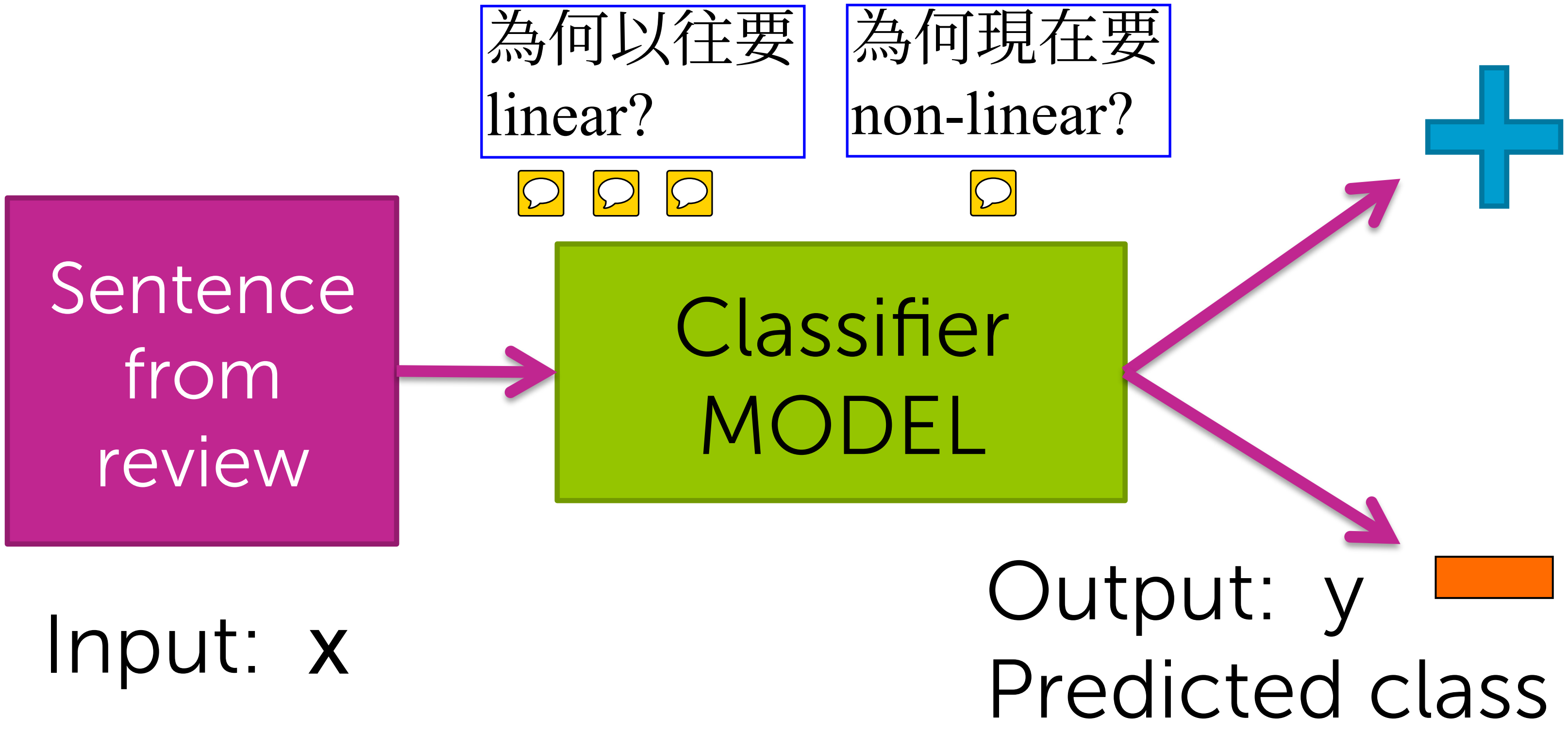
©2015 Emily Fox & Carlos Guestrin

Visual product search demo

當你決定目的、擁有資料、並決定用 machine learning 的當下

Features are key to machine learning

Goal: revisit classifiers, but using more complex, non-linear features



©2015 Emily Fox & Carlos Guestrin

Image classification

Input: x
Image pixels

Output: y
Predicted object

©2015 Emily Fox & Carlos Guestrin

Neural networks

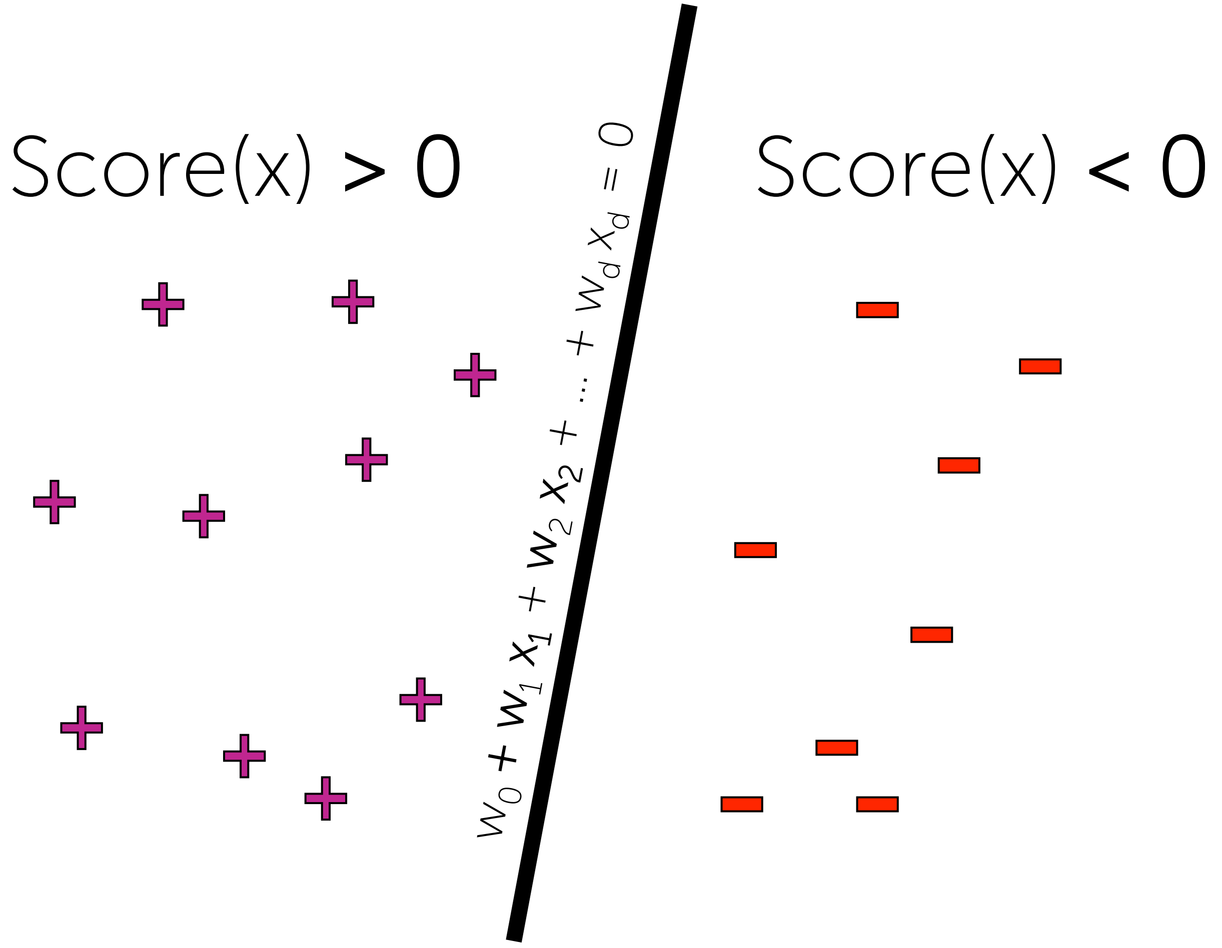
↓

Learning *very* non-linear features

參照 Andrew 的 machine learning
Week 4 & 5

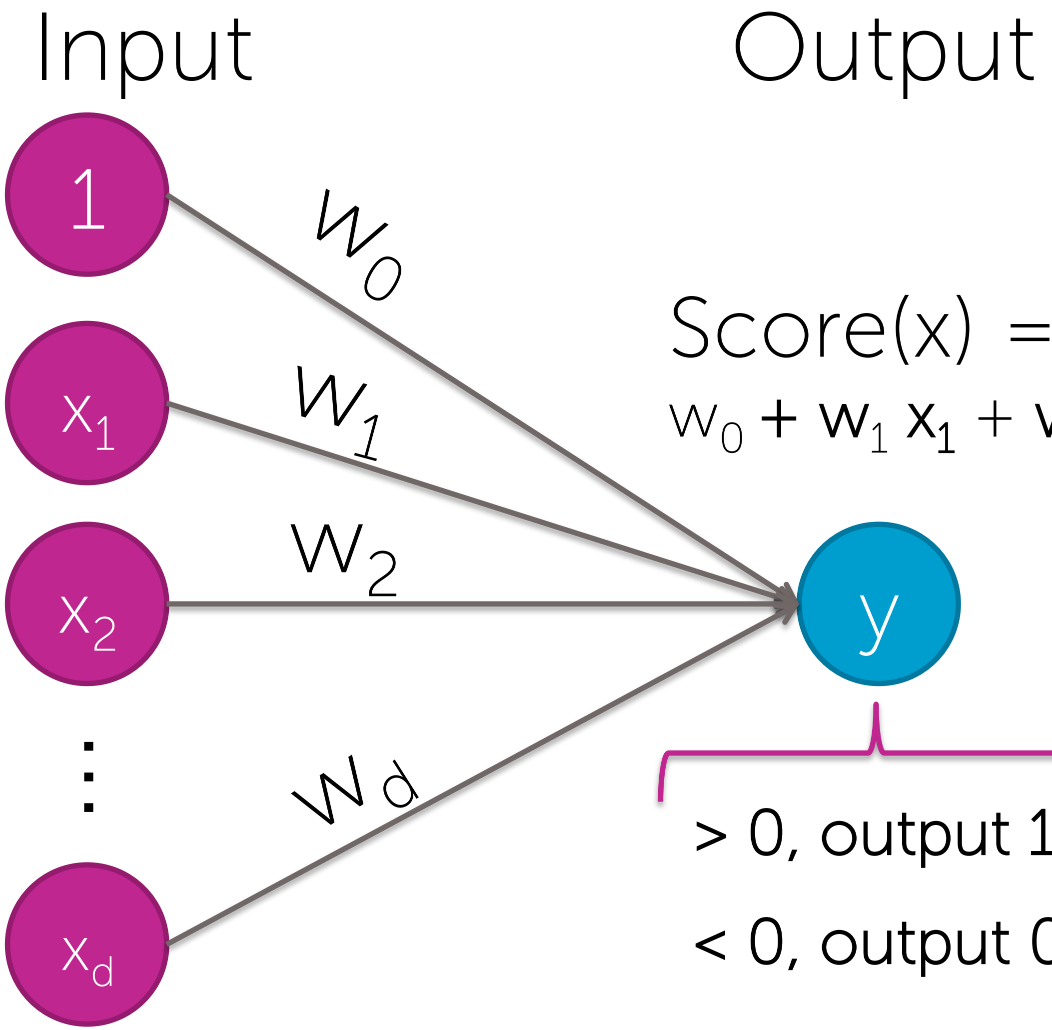
Linear classifiers

$$\text{Score}(x) = w_0 + w_1 x_1 + w_2 x_2 + \ldots + w_d x_d$$



©2015 Emily Fox & Carlos Guestrin

Graph representation of classifier: useful for defining neural networks



$$Score(x) = w_0 + w_1 x_1 + w_2 x_2 + \ldots + w_d x_d$$

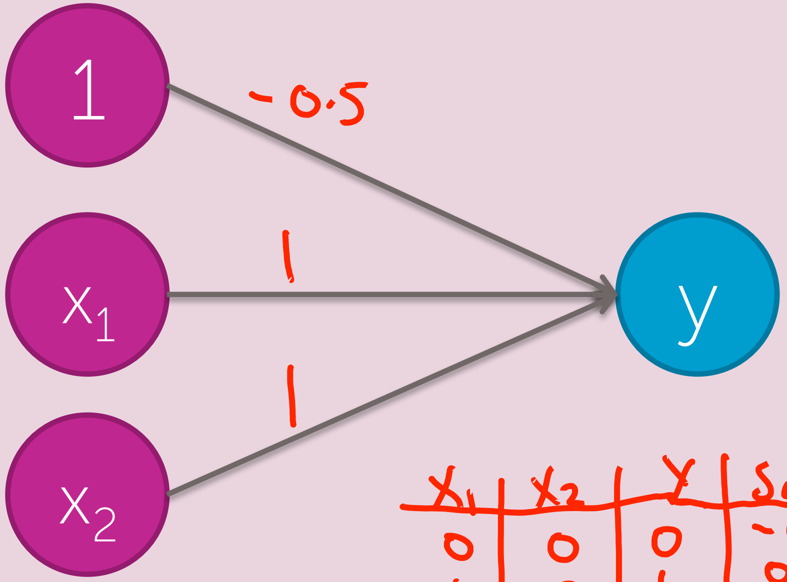
> 0, output 1

< 0, output 0

©2015 Emily Fox & Carlos Guestrin

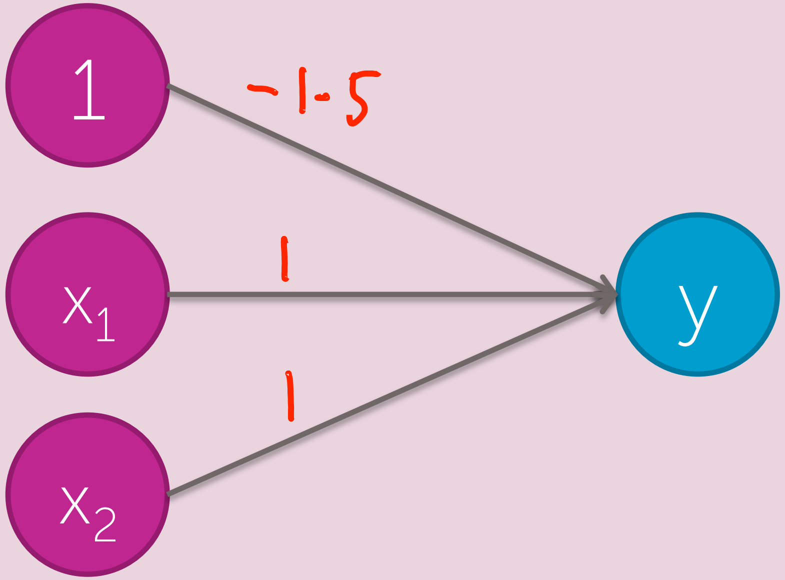
What can a linear classifier represent?

x_1 OR x_2



x_1	x_2	y	Score
0	0	0	-0.5
1	0	1	0.5
0	1	1	0.5
1	1	1	1.5

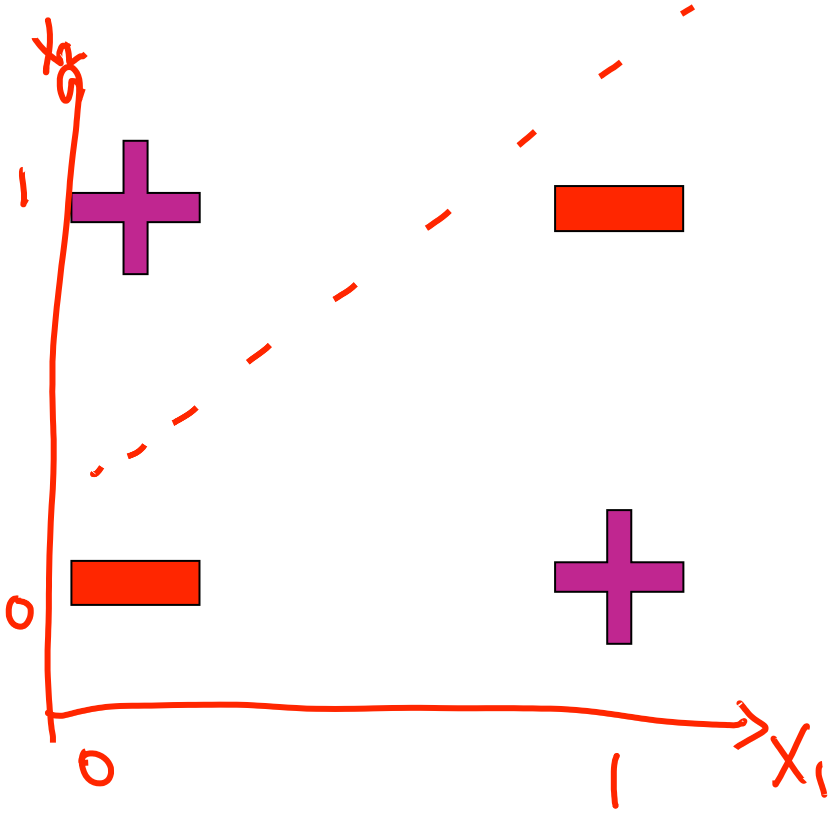
x_1 AND x_2



©2015 Emily Fox & Carlos Guestrin

What can't a simple linear classifier represent?

需要找例子的時候
先想想 XOR



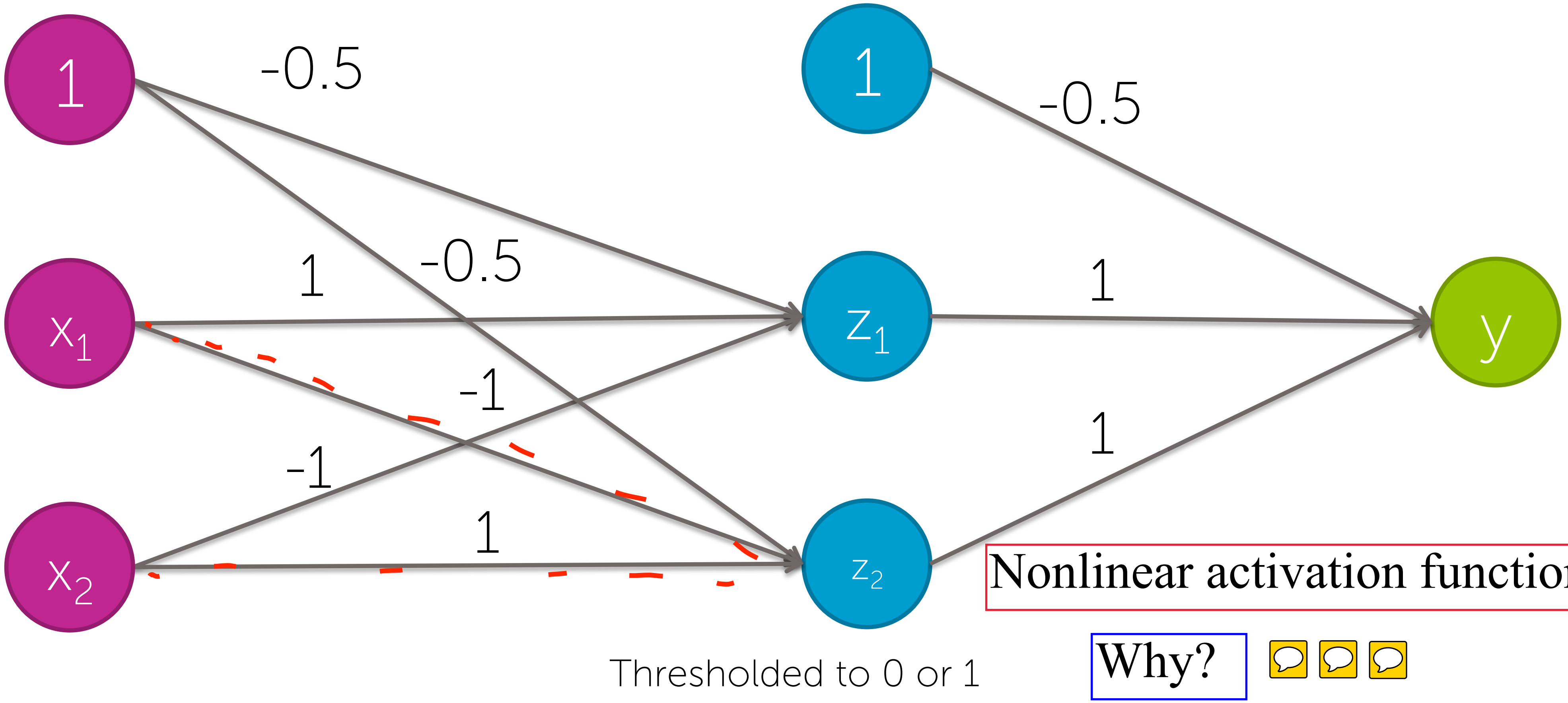
XOR
the counterexample to everything

Need non-linear features

©2015 Emily Fox & Carlos Guestrin

Solving the XOR problem: Adding a layer

$$\text{XOR} = \underbrace{x_1 \text{ AND NOT } x_2}_{z_1} \text{ OR } \underbrace{\text{NOT } x_1 \text{ AND } x_2}_{z_2}$$



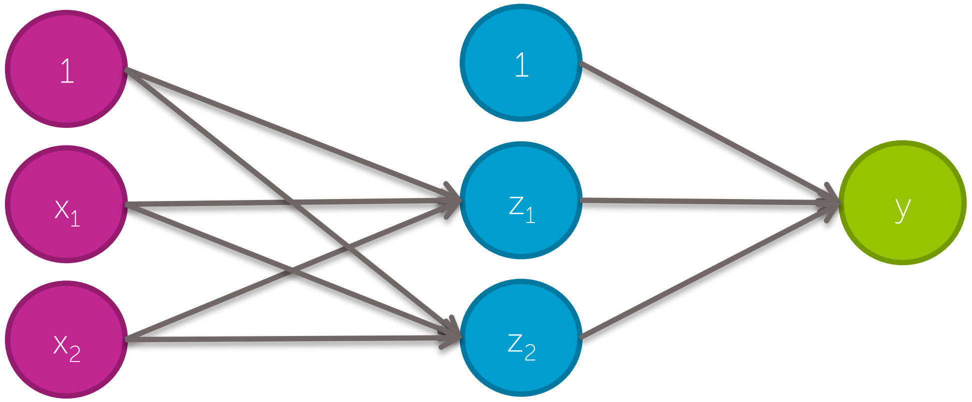
Nonlinear activation function

Why?

©2015 Emily Fox & Carlos Guestrin

A neural network

- Layers and layers and layers of linear models and non-linear transformations



- Around for about 50 years
  - Fell in "disfavor" in 90s
- In last few years, big resurgence
  - Impressive accuracy on several benchmark problems
  - Powered by huge datasets, GPUs, & modeling/learning alg improvements

©2015 Emily Fox & Carlos Guestrin

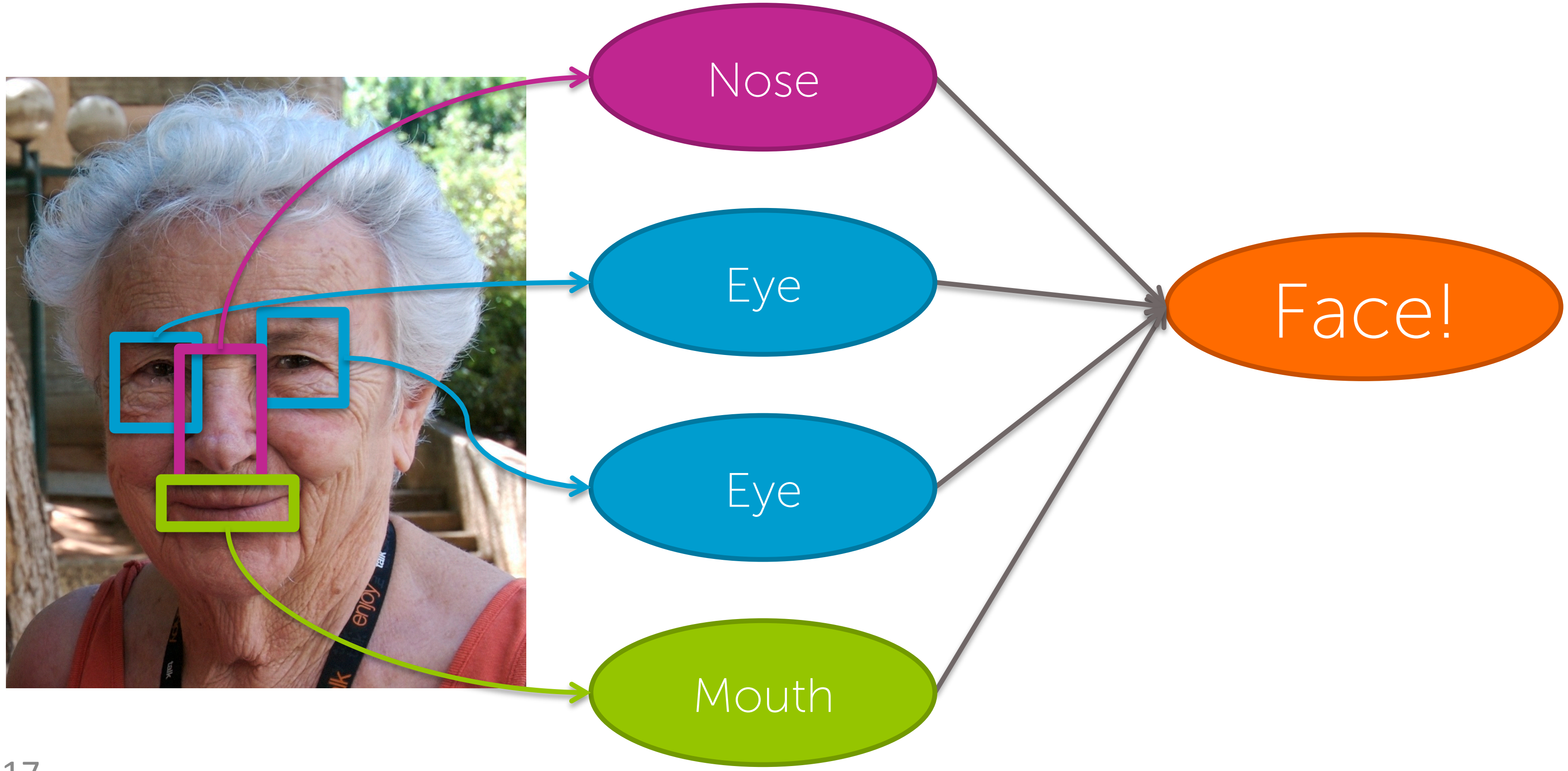
Application of deep learning to computer vision

參照 Andrew 的 deep learning
part 1 & 2

©2015 Emily Fox & Carlos Guestrin

Image features

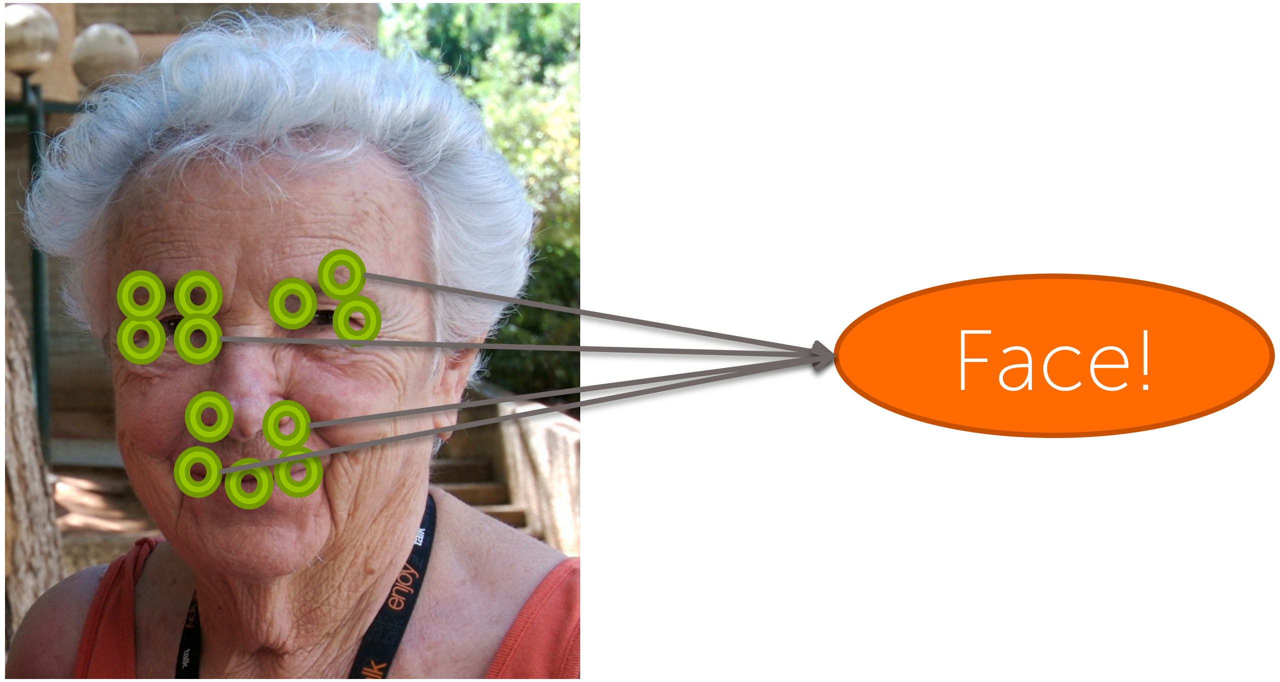
- Features = local detectors
  - Combined to make prediction
  - (in reality, features are more low-level)



©2015 Emily Fox & Carlos Guestrin

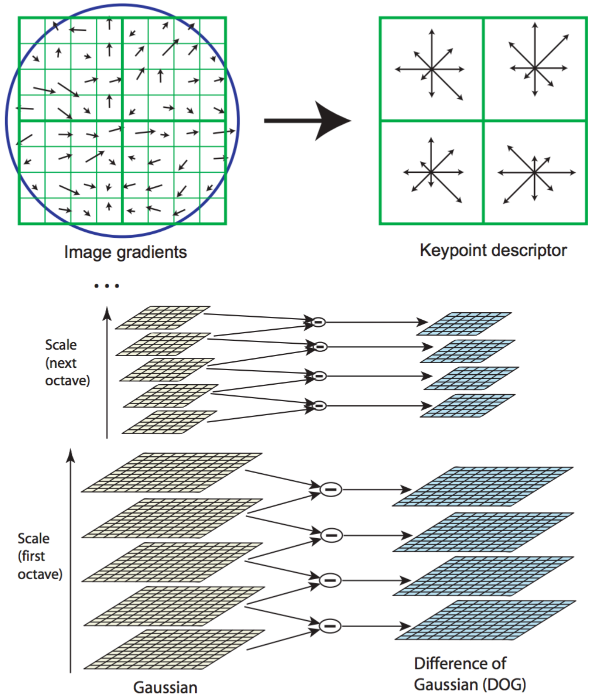
Typical local detectors look for locally "interesting points" in image

- *Image features*: collections of locally interesting points
  - Combined to build classifiers



©2015 Emily Fox & Carlos Guestrin

Many hand created features exist for finding interest points…



SIFT [Lowe '99]

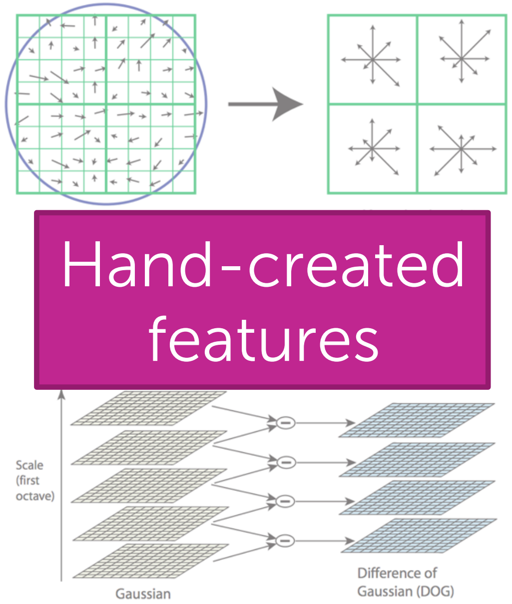
- *Spin Images* [Johnson & Herbert '99]
- *Textons* [Malik et al. '99]
- *RIFT* [Lazebnik '04]
- *GLOH* [Mikolajczyk & Schmid '05]
- *HoG* [Dalal & Triggs '05]
- …

©2015 Emily Fox & Carlos Guestrin

Standard image classification approach

Input

Extract features



Hand-created features

0 0 1 0 0 1 1 0 0 0

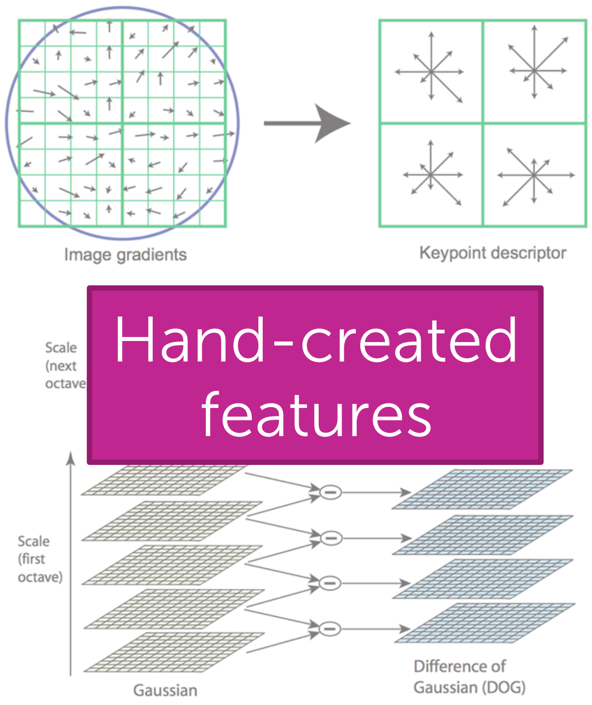
Use simple classifier

e.g., logistic regression, SVMs

Face?

©2015 Emily Fox & Carlos Guestrin

Many hand created features exist for finding interest points…



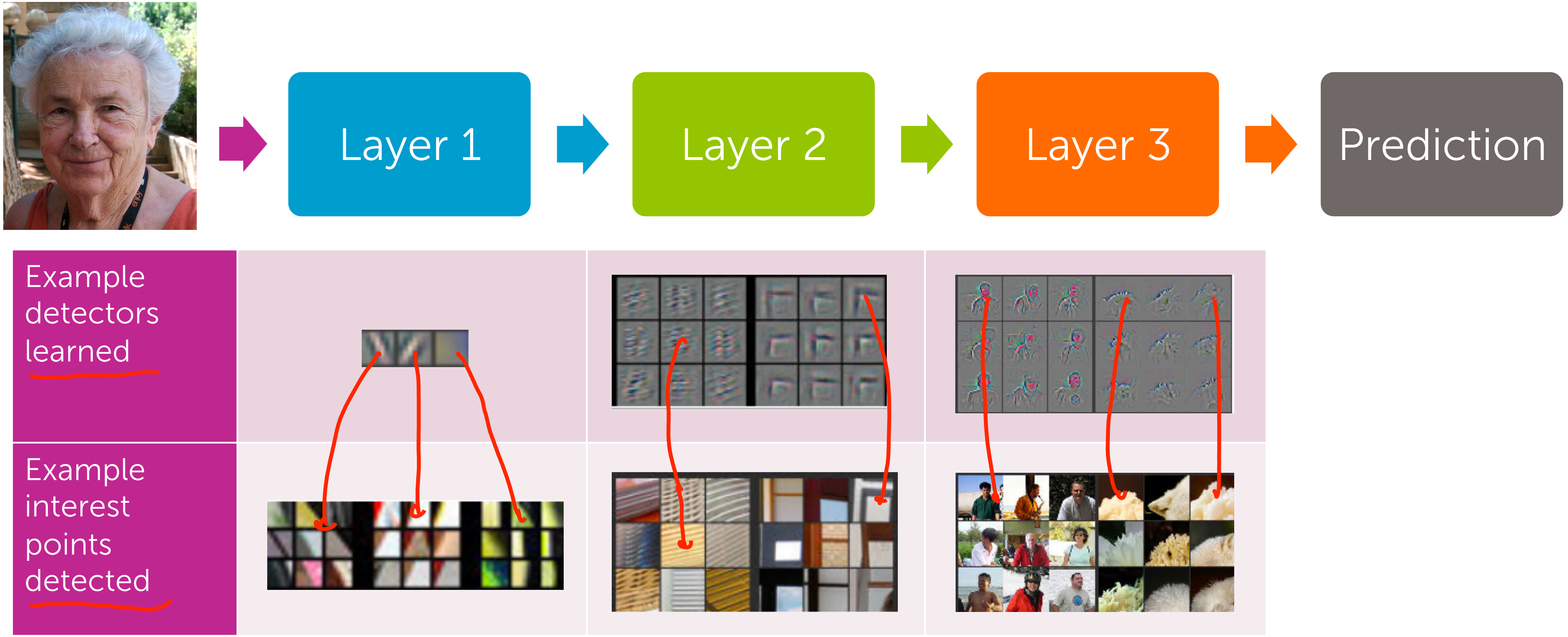
SIFT [Lowe '99]

- *Spin Images* [Johnson & Herbert '99]
- *Textons* [Malik et al. '99]
- *RIFT* [Lazebnik '04]
- *GLOH* [Mikolajczyk & Schmid '05]
- *HoG* [Dalal & Triggs '05]
- …

… but very painful to design

©2015 Emily Fox & Carlos Guestrin

Deep learning:
implicitly learns features



[Zeiler & Fergus '13]

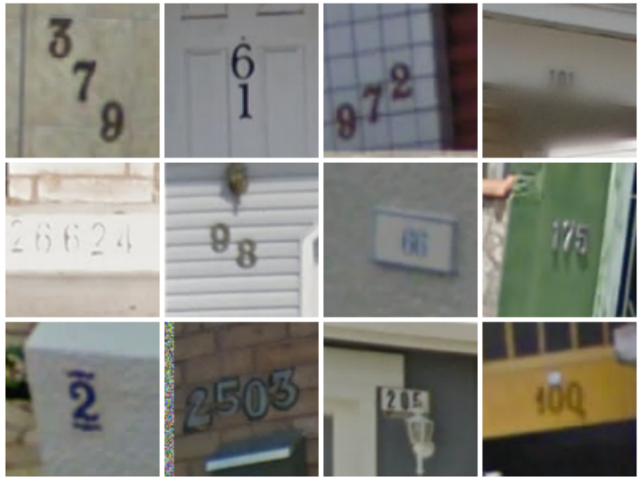
©2015 Emily Fox & Carlos Guestrin

Deep learning performance

Sample results using deep neural networks

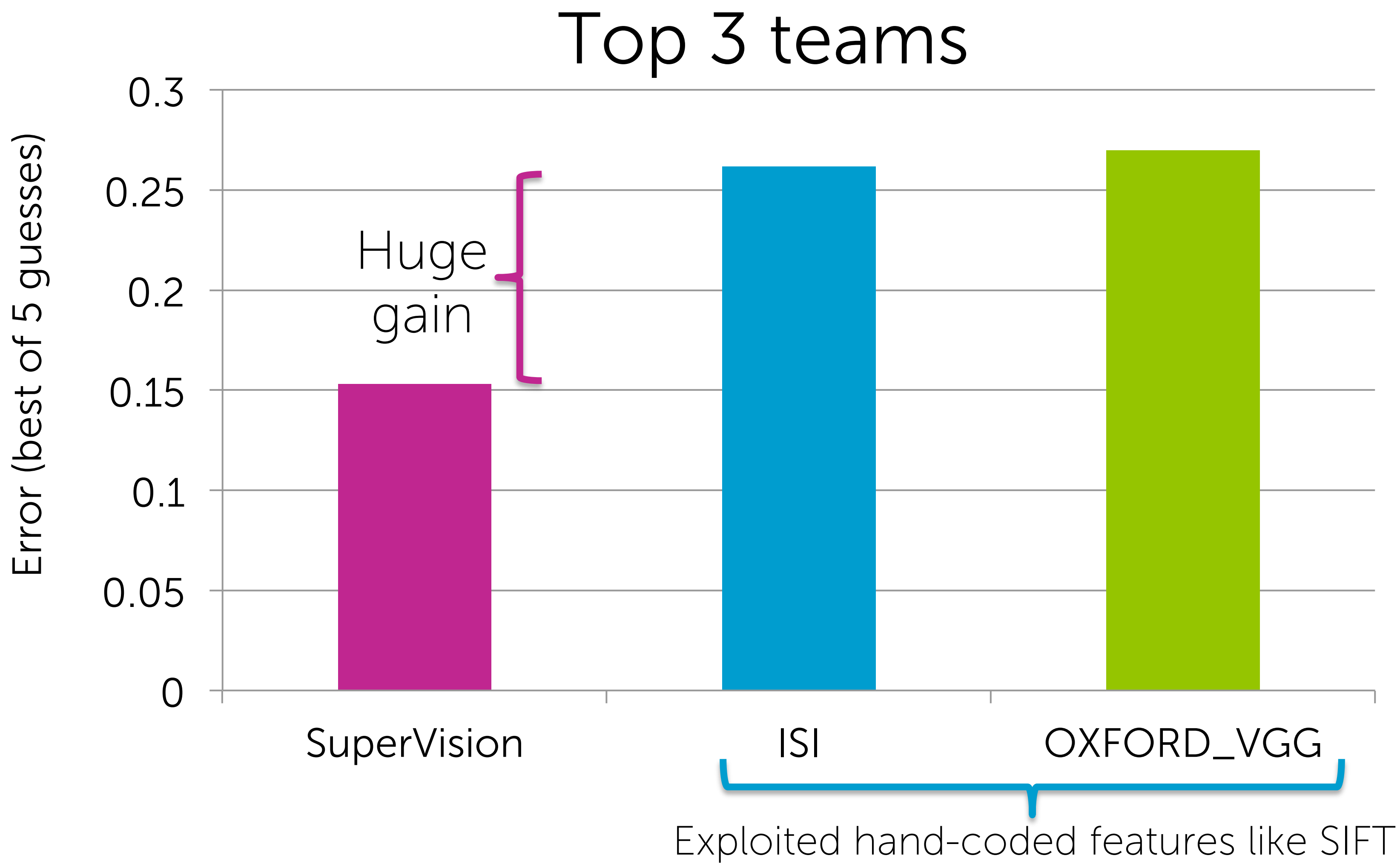
- German traffic sign recognition benchmark
  - 99.5% accuracy (IDSIA team)

- House number recognition
  - 97.8% accuracy per character [Goodfellow et al. '13]



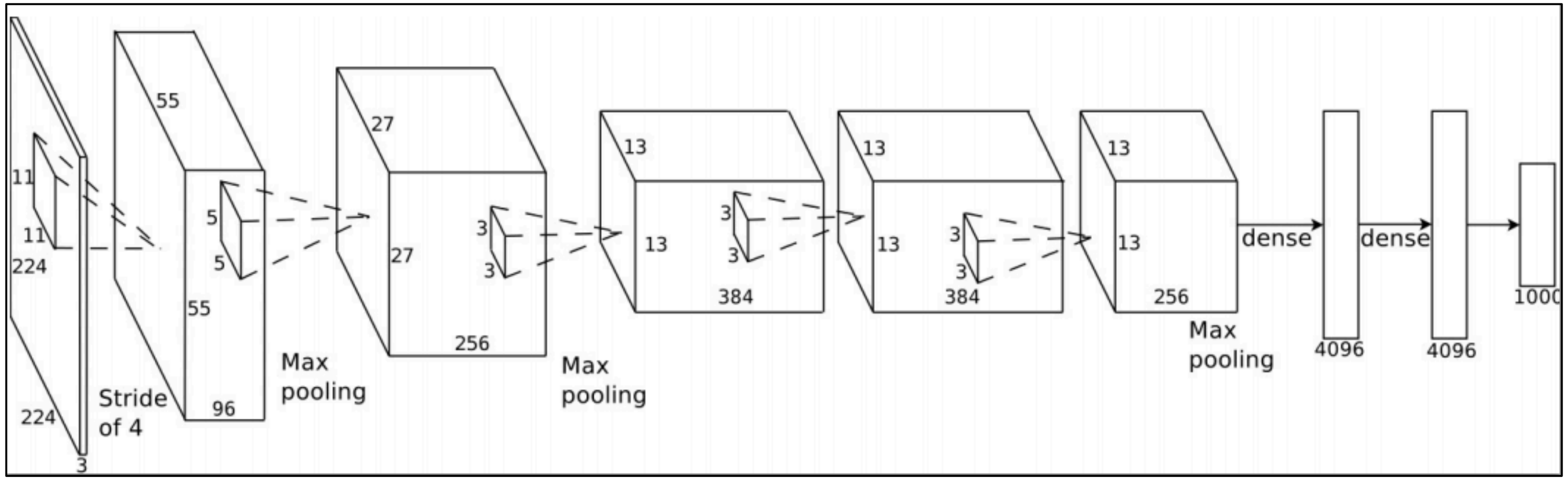
©2015 Emily Fox & Carlos Guestrin

ImageNet 2012 competition: 1.2M training images, 1000 categories



ImageNet 2012 competition: 1.2M training images, 1000 categories

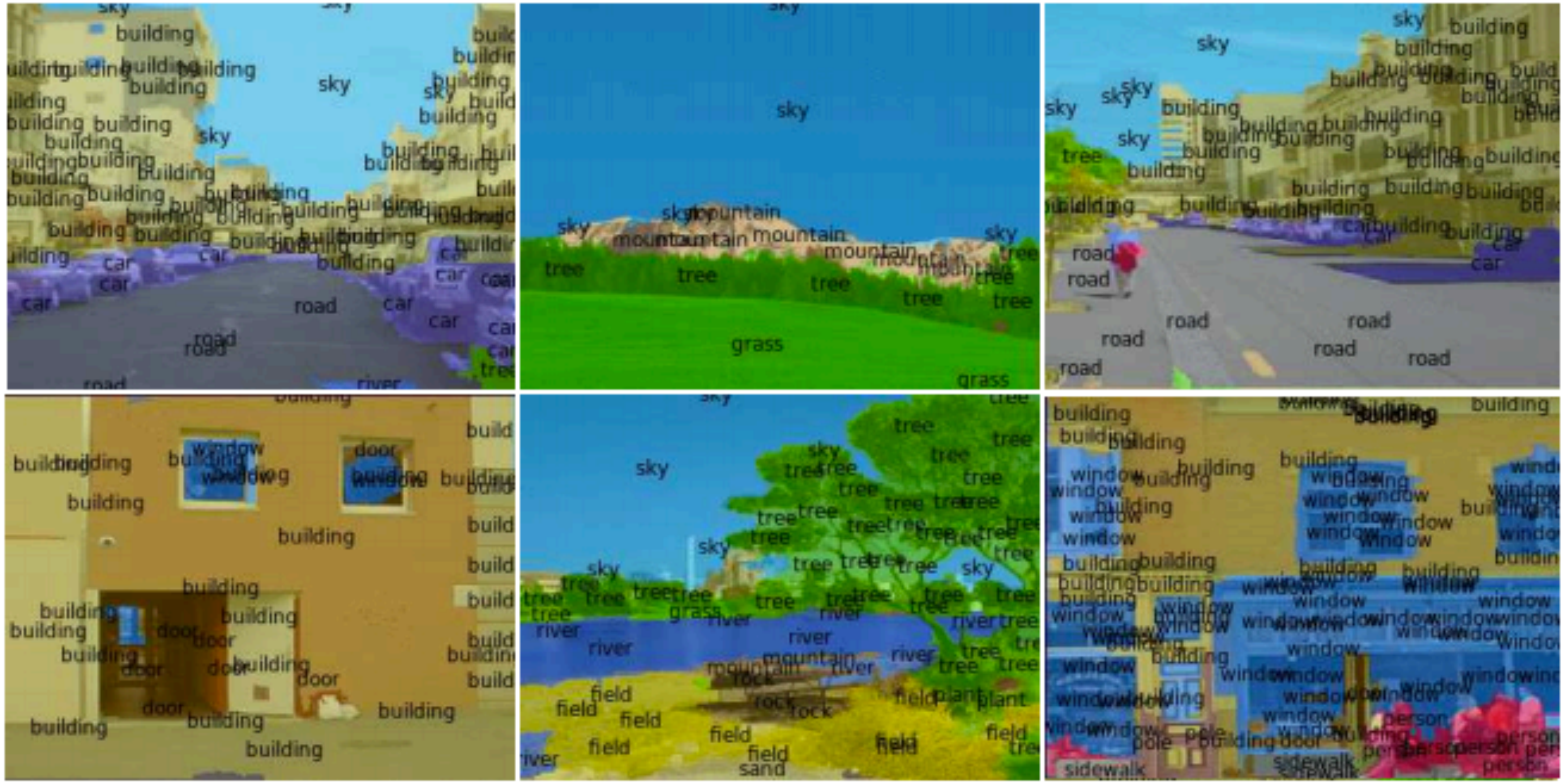
Winning entry: SuperVision
8 layers, 60M parameters [Krizhevsky et al. '12]



Achieving these amazing results required:
- New learning algorithms
- GPU implementation

Deep learning in computer vision

Scene parsing with deep learning



[Farabet et al. '13]

©2015 Emily Fox & Carlos Guestrin

Retrieving similar images

Input Image | Nearest neighbors

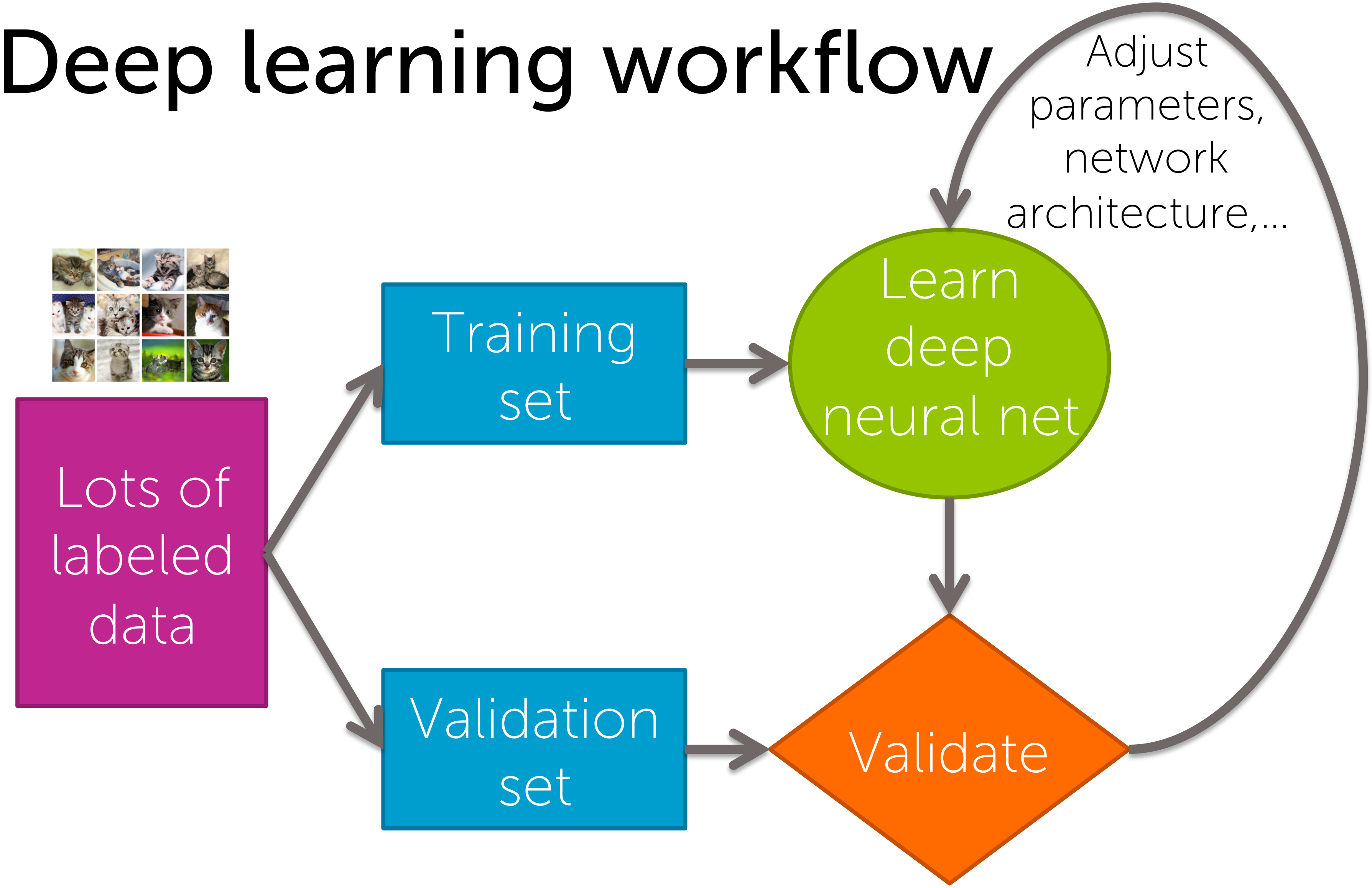
Challenges of deep learning

Deep learning score card

Pros

- Enables learning of features rather than hand tuning
- Impressive performance gains
  - Computer vision
  - Speech recognition
  - Some text analysis
- Potential for more impact

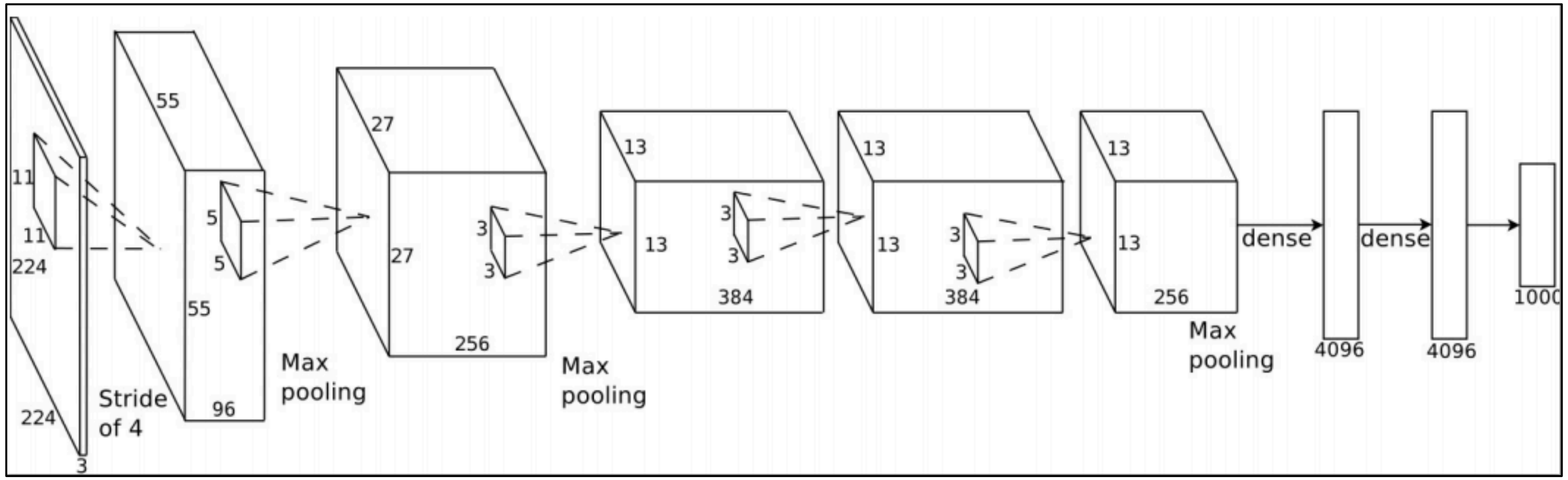
Deep learning workflow



Many tricks needed to work well…

參照 Andrew 的 deep learning part 4 & 5

Different types of layers, connections,… needed for high accuracy



[Krizhevsky et al. '12]

©2015 Emily Fox & Carlos Guestrin

Deep learning score card

Pros

- Enables learning of features rather than hand tuning
- Impressive performance gains
  - Computer vision
  - Speech recognition
  - Some text analysis
- Potential for more impact

Cons

- Requires a lot of data for high accuracy
- Computationally really expensive
- Extremely hard to tune
  - Choice of architecture
  - Parameter types
  - Hyperparameters
  - Learning algorithm
  - …

Computational cost+ so many choices
=
incredibly hard to tune

參照 Andrew 的 deep learning part 2 & 3

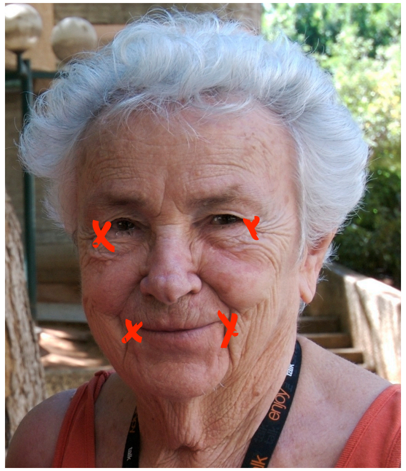
Deep features:

参照 Andrew 的 deep learning
part 3, week 2
Learning from multiple tasks
End-to-end deep learning

Deep learning
+
Transfer learning

Standard image classification approach

Input



Extract features

Can we learn features from data, even when we don't have data or time?

Use simple classifier

e.g., logistic regression, SVMs

Face?

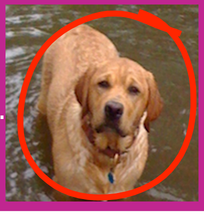
©2015 Emily Fox & Carlos Guestrin

Transfer learning: *Use data from one task to help learn on another*

Old idea, explored for deep learning by Donahue et al. '14 & others

Lots of data:

vs.



Learn neural net

Great accuracy on cat v. dog

Some data:

Neural net as feature extractor

+

Simple classifier

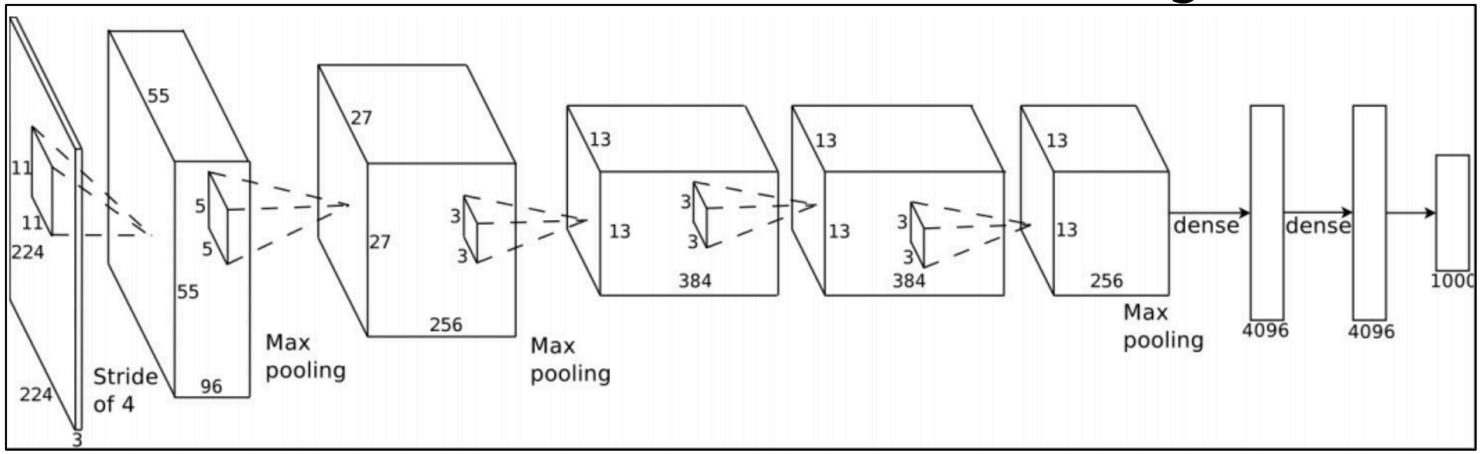
Great accuracy on 101 categories

©2015 Emily Fox & Carlos Guestrin

What's learned in a neural net

Neural net trained for Task 1: cat vs. dog

vs.



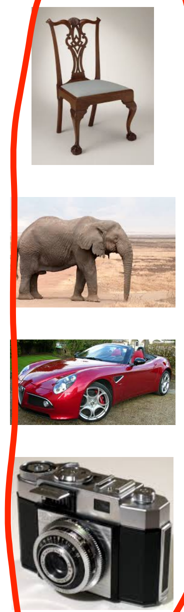
More generic
Can be used as feature extractor

Very specific
to Task 1
Should be ignored
for other tasks

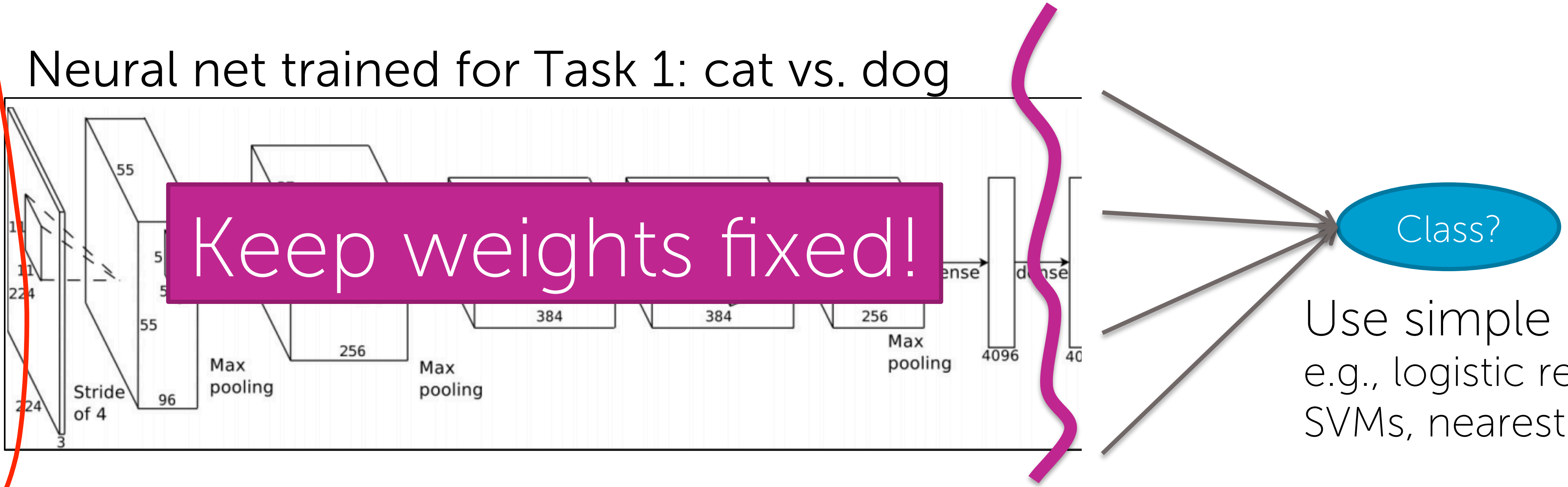
©2015 Emily Fox & Carlos Guestrin

Transfer learning in more detail…

For Task 2, predicting 101 categories,
learn only end part of neural net



Neural net trained for Task 1: cat vs. dog



Use simple classifier
e.g., logistic regression,
SVMs, nearest neighbor,…

More generic
Can be used as feature extractor

~~Very specific
to Task 1
Should be ignored
for other tasks~~

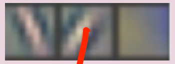
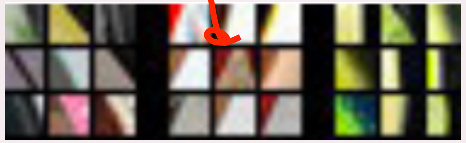
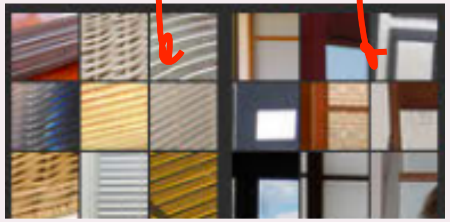
©2015 Emily Fox & Carlos Guestrin

Careful where you cut:
latter layers may be too task specific

Use these!

Too specific for new task

Layer 1 → Layer 2 → Layer 3 → Prediction

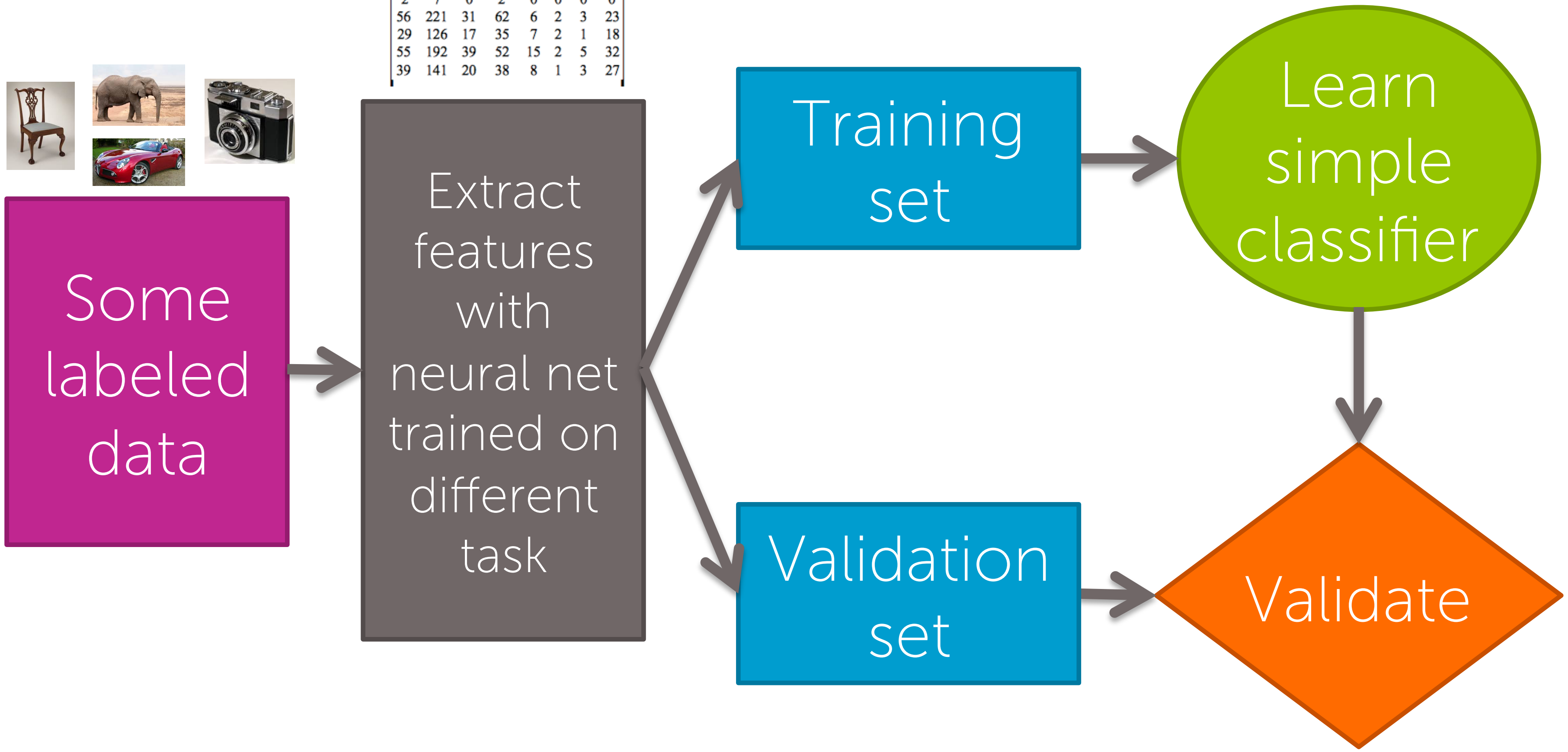
	Layer 1	Layer 2	Layer 3
Example detectors learned			
Example interest points detected			

[Zeiler & Fergus '13]

©2015 Emily Fox & Carlos Guestrin

Transfer learning with deep features workflow

$$
H=\begin{bmatrix}
20 & 77 & 21 & 31 & 4 & 5 & 1 & 13\\
35 & 141 & 26 & 46 & 9 & 0 & 4 & 28\\
76 & 301 & 49 & 91 & 23 & 2 & 7 & 43\\
70 & 280 & 53 & 84 & 21 & 5 & 10 & 54\\
71 & 258 & 44 & 76 & 19 & 4 & 4 & 32\\
21 & 86 & 12 & 25 & 5 & 0 & 4 & 22\\
92 & 350 & 53 & 102 & 19 & 1 & 5 & 40\\
2 & 7 & 0 & 2 & 0 & 0 & 0 & 0\\
56 & 221 & 31 & 62 & 6 & 2 & 3 & 23\\
29 & 126 & 17 & 35 & 7 & 2 & 1 & 18\\
55 & 192 & 39 & 52 & 15 & 2 & 5 & 32\\
39 & 141 & 20 & 38 & 8 & 1 & 3 & 27
\end{bmatrix}
$$



How general are deep features?

compology

Summary of deep learning

What you can do now…

- Describe multi-layer neural network models
- Interpret the role of features as local detectors in computer vision
- Relate neural networks to hand-crafted image features
- Describe some settings where deep learning achieves significant performance boosts
- State the pros & cons of deep learning model
- Apply the notion of transfer learning
- Use neural network models trained in one domain as features for building a model in another domain
- Build an image retrieval tool using deep features

©2015 Emily Fox & Carlos Guestrin