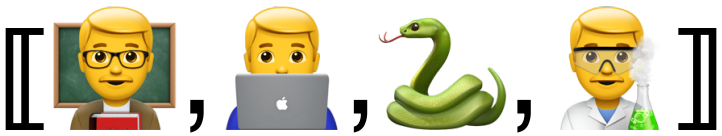
Lecture Notes for

Machine Learning in Python



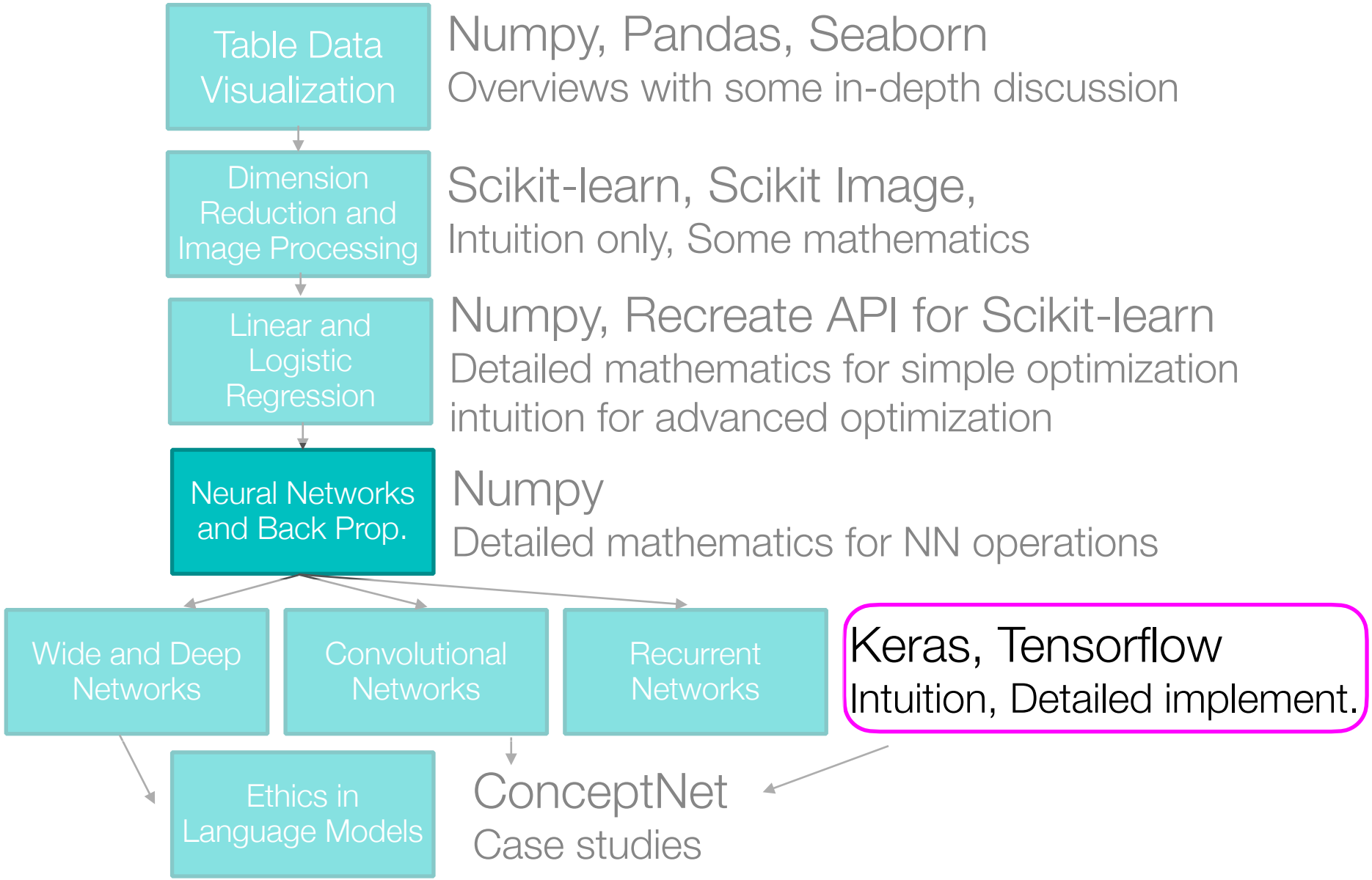
Revisiting Cross Validation

A "Too Early" History of Deep Learning

Logistics and Agenda

- Logistics
  - Grading update
- Agenda
  - Revisiting Cross Validation
  - Town Hall
  - “Deep Learning” History

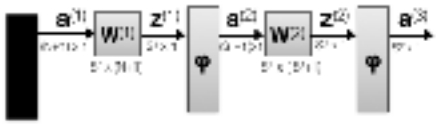
Class Overview, by topic



Last time:

Back propagation summary

$$J(\mathbf{W}) = \sum_{k}^{M} (\mathbf{y}^{(k)} - \mathbf{a}^{(L)})^2$$



$$w_{ij}^{(l)} \leftarrow w_{ij}^{(l)} - \eta \frac{\partial J(\mathbf{W})}{\partial \mathbf{z}^{(l)}} a_j^{(l)}$$

1. Forward propagate to get $\mathbf{z}$, $\mathbf{a}$ for all layers
2. Get final layer gradient
3. Update back propagation variables
4. Update each $\mathbf{W}^{(l)}$

for each $\mathbf{y}^{(i)}$

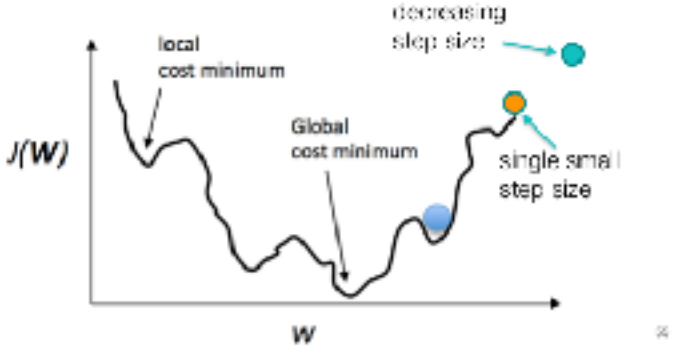
$$\frac{\partial J(\mathbf{W})}{\partial \mathbf{z}^{(2)}} = -2(\mathbf{y}^{(i)} - \mathbf{a}^{(3)}) * \mathbf{a}^{(3)} * (1 - \mathbf{a}^{(3)})$$

$$\frac{\partial J(\mathbf{W})}{\partial \mathbf{z}^{(l)}} = \text{diag}[\mathbf{a}^{(l+1)} * (1 - \mathbf{a}^{(l+1)})] \cdot \mathbf{W}^{(l+1)} \frac{\partial J(\mathbf{W})}{\partial \mathbf{z}^{(l+1)}}$$

$$\mathbf{W}^{(l)} \leftarrow \mathbf{W}^{(l)} - \eta \frac{\partial J(\mathbf{W}^{(l)})}{\partial \mathbf{z}^{(l)}} \cdot \mathbf{a}^{(l)}$$

Problems with Advanced Architectures

- Space is no longer convex
  - **One solution:**
    - start with large step size
    - "cool down" by decreasing step size for higher iterations



Practical Implementation of Architectures

- A new cost function: **Cross entropy**

$$J(\mathbf{W}) = -[\mathbf{y}^{(i)} \ln \mathbf{a}^{(L)} + (1 - \mathbf{y}^{(i)}) \ln(1 - \mathbf{a}^{(L)})]$$

speeds up initial training

$$\frac{\partial J(\mathbf{W})}{\partial \mathbf{z}^{(L)}} = (_i\mathbf{a}^{(L+1)} - \mathbf{y}^{(i)})$$

$$\frac{\partial J(\mathbf{W})}{\partial \mathbf{z}^{(2)}} = (_i\mathbf{a}^{(3)} - \mathbf{y}^{(i)})$$

```
# vectorized backpropagation
sigma3 = (A3-Y_enc) # <- this is only line
sigma2 = (W2.T @ sigma3)*A2*(1-A2)

grad1 = sigma2[1:,:] @ A1
grad2 = sigma3 @ A2.T
```

new update

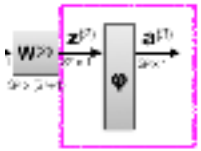
```
# vectorized backpropagation
sigma3 = -2*(Y_enc-A3)*A3*(1-A3)
sigma2 = (W2.T @ sigma3)*A2*(1-A2)

grad1 = sigma2[1:,:] @ A1
grad2 = sigma3 @ A2.T
```

$$\frac{\partial J(\mathbf{W})}{\partial \mathbf{z}^{(2)}} = -2(\mathbf{y}^{(i)} - \mathbf{a}^{(3)}) * \mathbf{a}^{(3)} * (1 - \mathbf{a}^{(3)})$$ old update

bp-5

Practical Implementation of Architectures

- A new nonlinearity: **recitifed linear units**

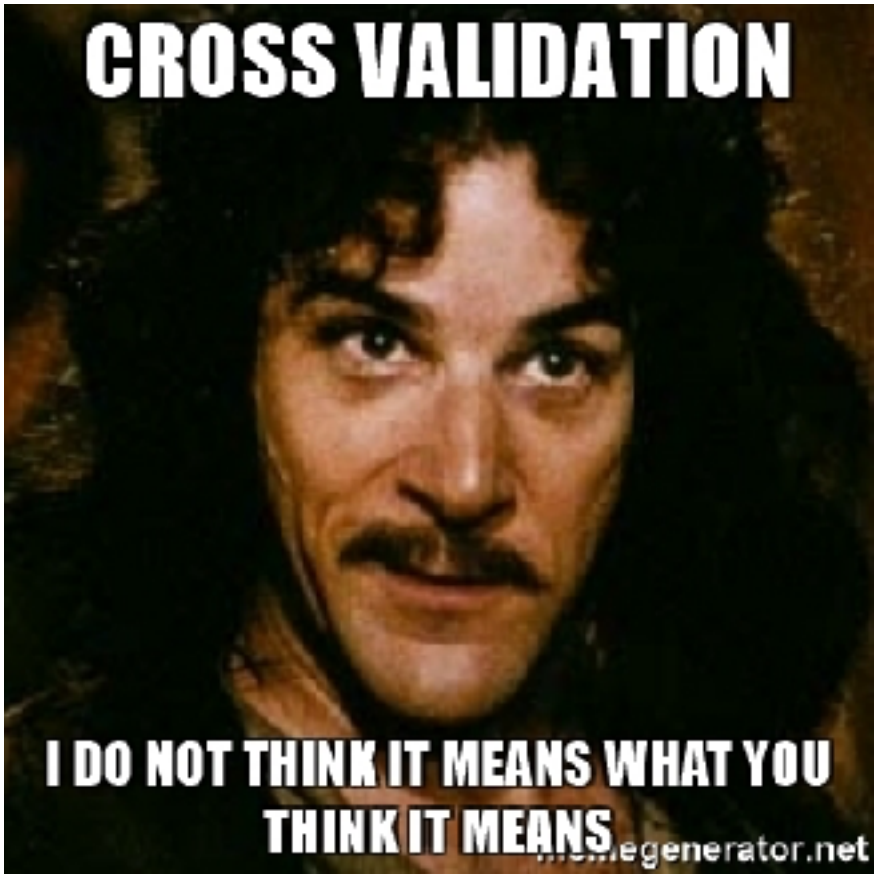


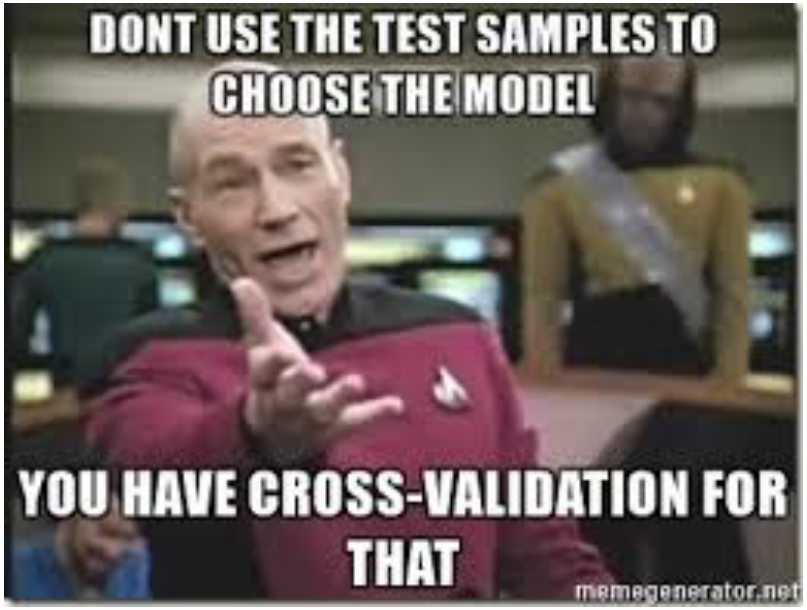
$$\phi(\mathbf{z}^{(i)}) = \begin{cases} \mathbf{z}^{(i)}, \text{ if } \mathbf{z}^{(i)} > 0 \\ \mathbf{0}, \text{ else} \end{cases}$$

it has the advantage of **large gradients** and **extremely simple** derivative

$$\frac{\partial \phi(\mathbf{z}^{(i)})}{\partial \mathbf{z}^{(i)}} = \begin{cases} \mathbf{1}, \text{ if } \mathbf{z}^{(i)} > 0 \\ \mathbf{0}, \text{ else} \end{cases}$$

Revisiting Cross Validation

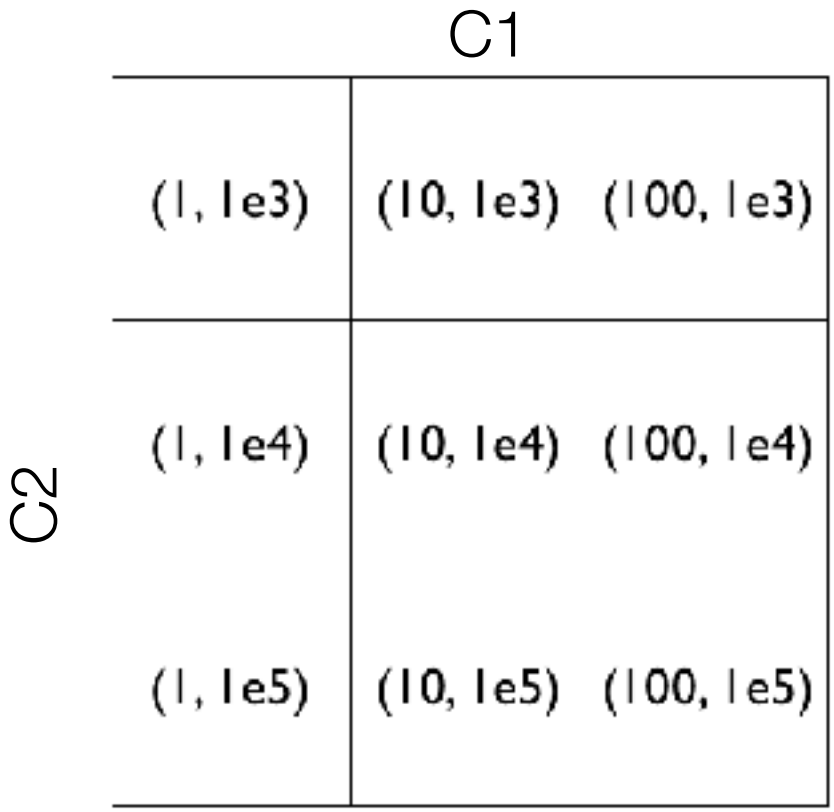




Review: Grid Searching

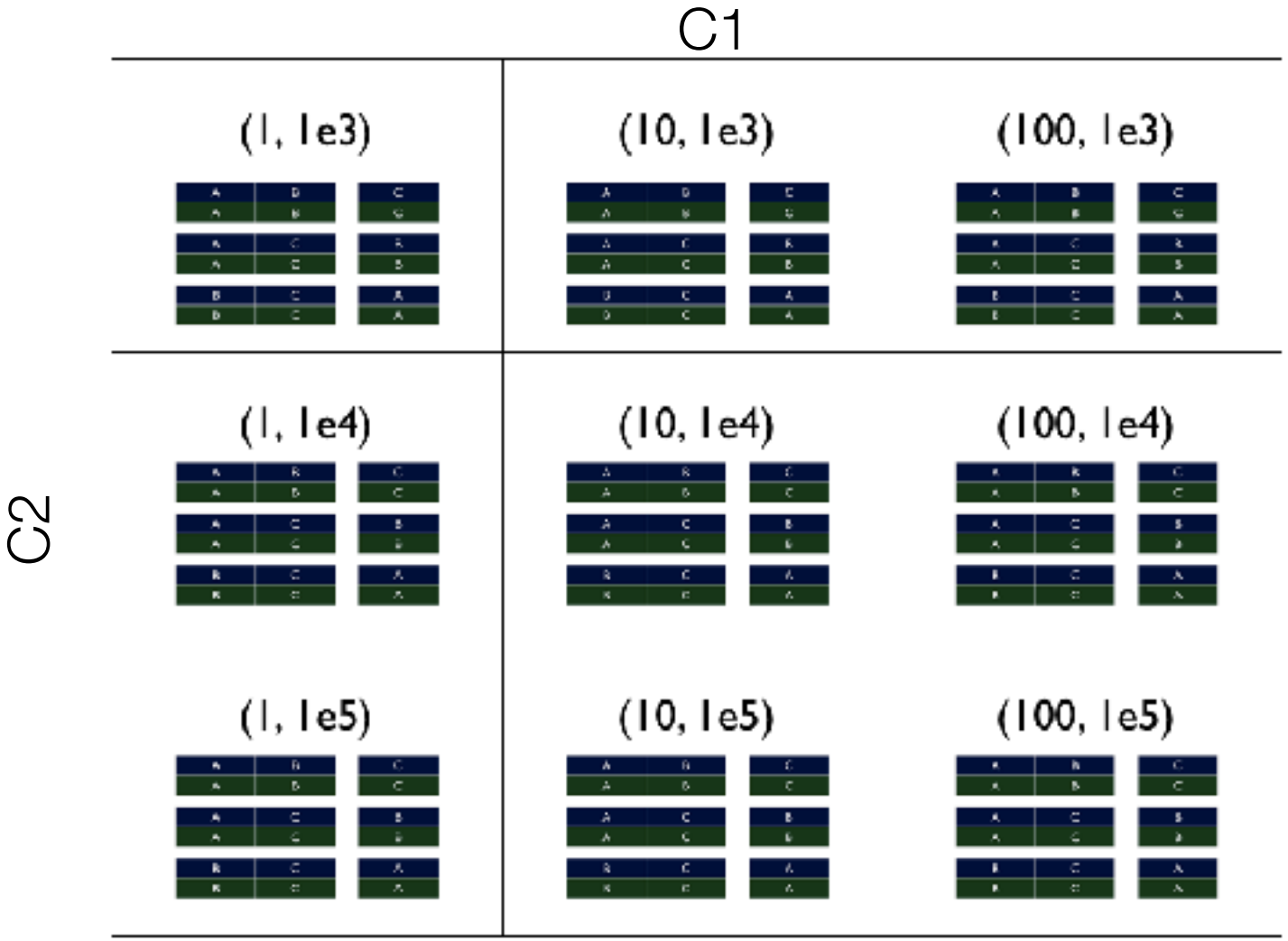
Trying to find the best parameters

```
NN: C1=[1, 10, 100] C2=[1e3,1e4,1e5]
```



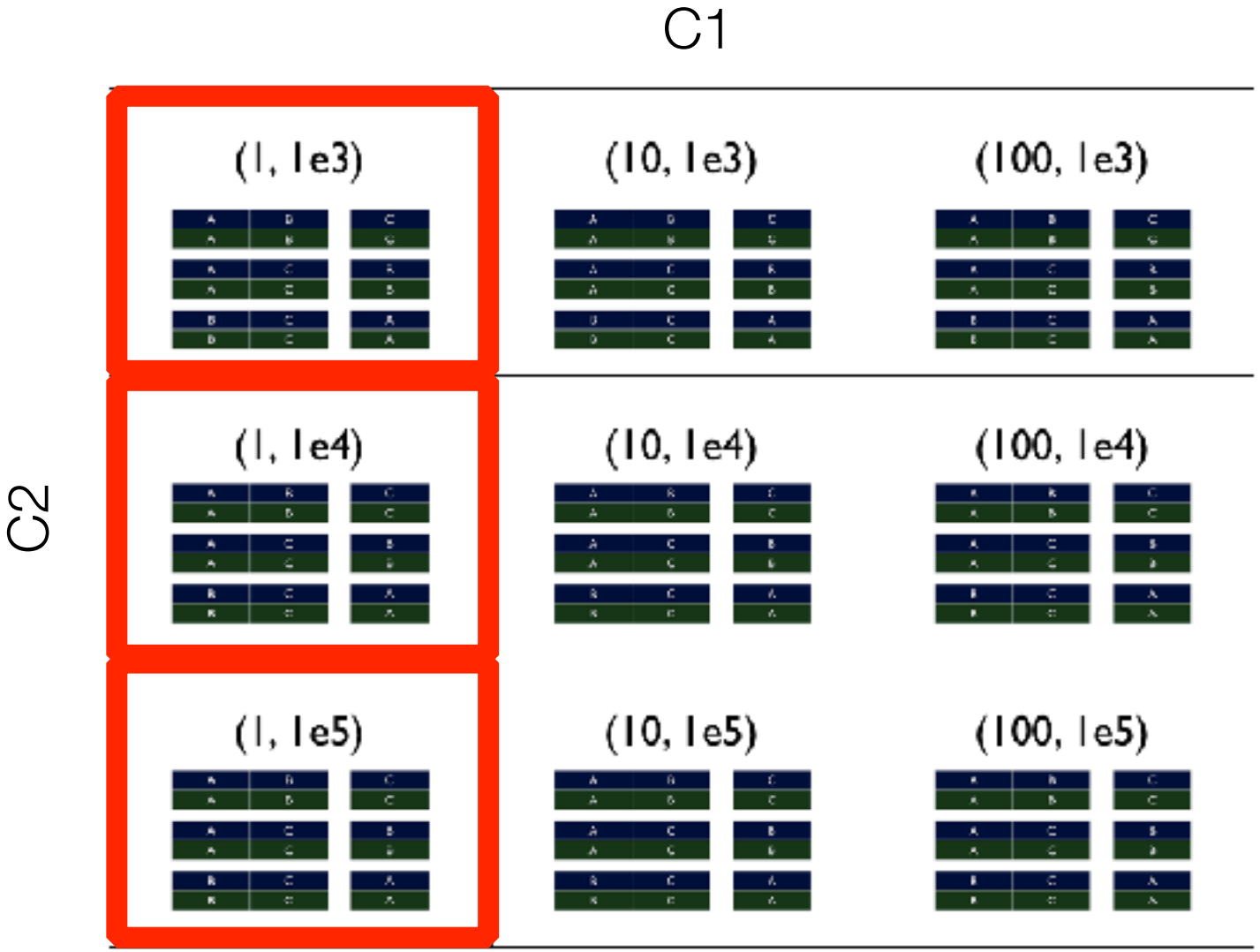
Review: Grid Searching

For each value, want to run cross validation…



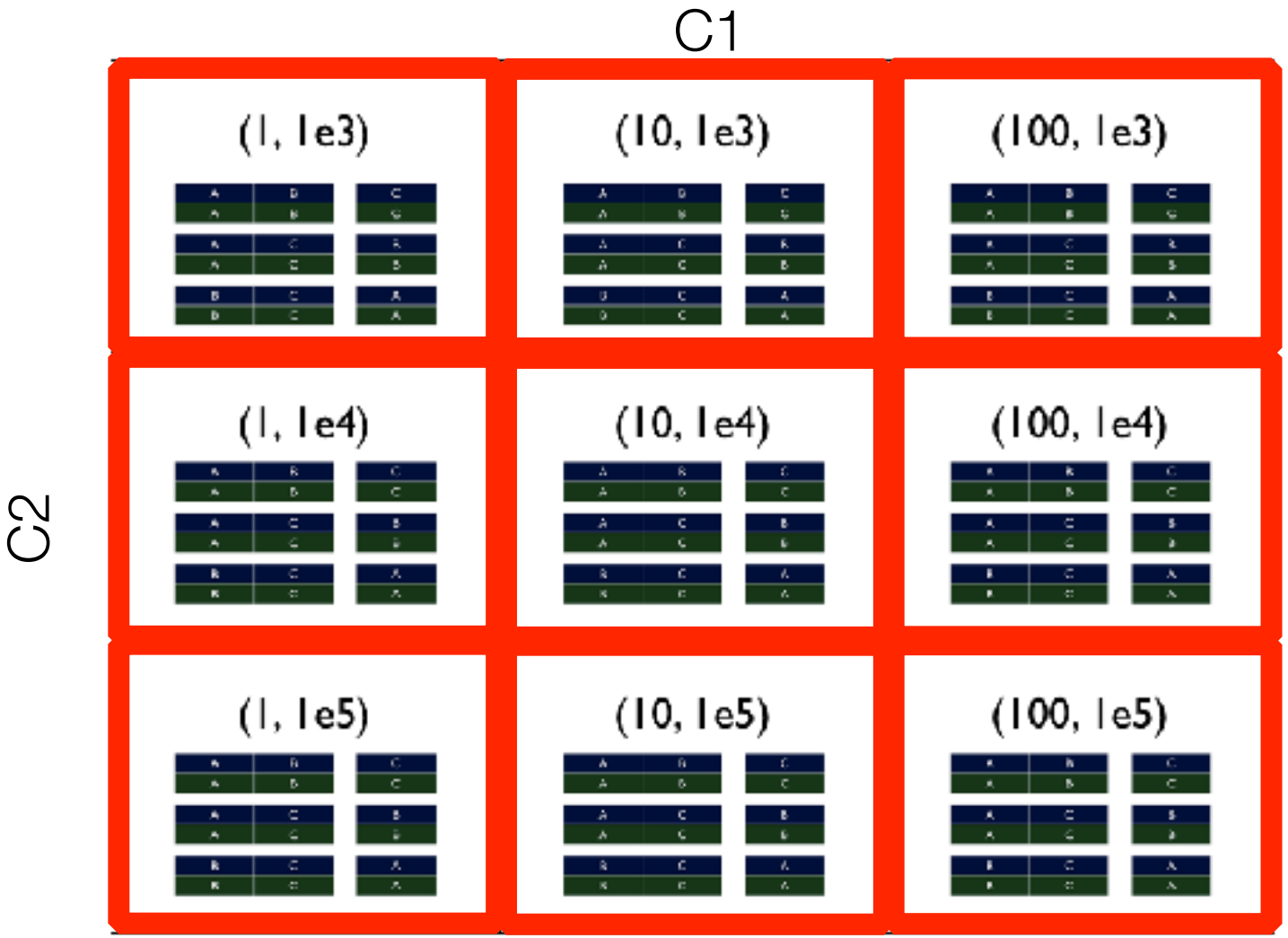
Review: Grid Searching

Could perform iteratively



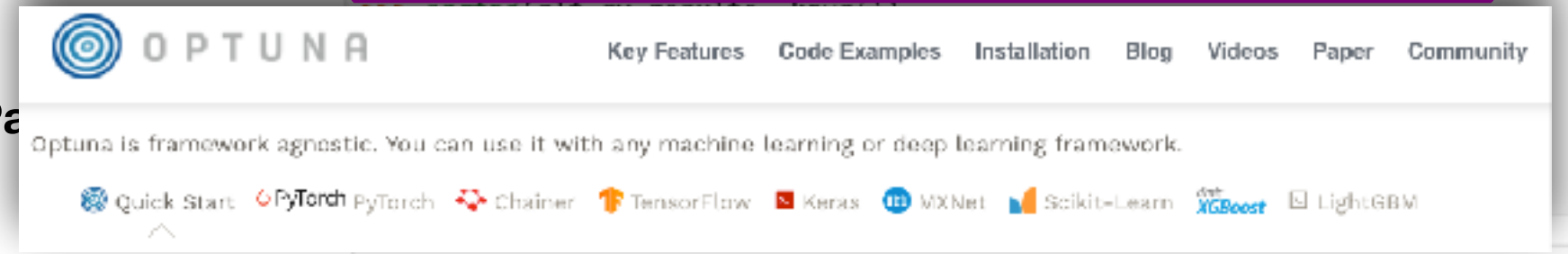
Review: Grid Searching

or at random…



Review: Grid Searches in Scikit-learn

```
>>> from sklearn import svm, datasets
>>> from sklearn.model_selection import GridSearchCV
>>> iris = datasets.load_iris()
>>> parameters = {'kernel':('linear', 'rbf'), 'C':[1, 10]}
>>> svc = svm.SVC()
>>> clf = GridSearchCV(svc, parameters)
>>> clf.fit(iris.data, iris.target)
GridSearchCV(estimator=SVC(),
             param_grid={'C': [1, 10], 'kernel': ('linear', 'rbf')})
```



Pa

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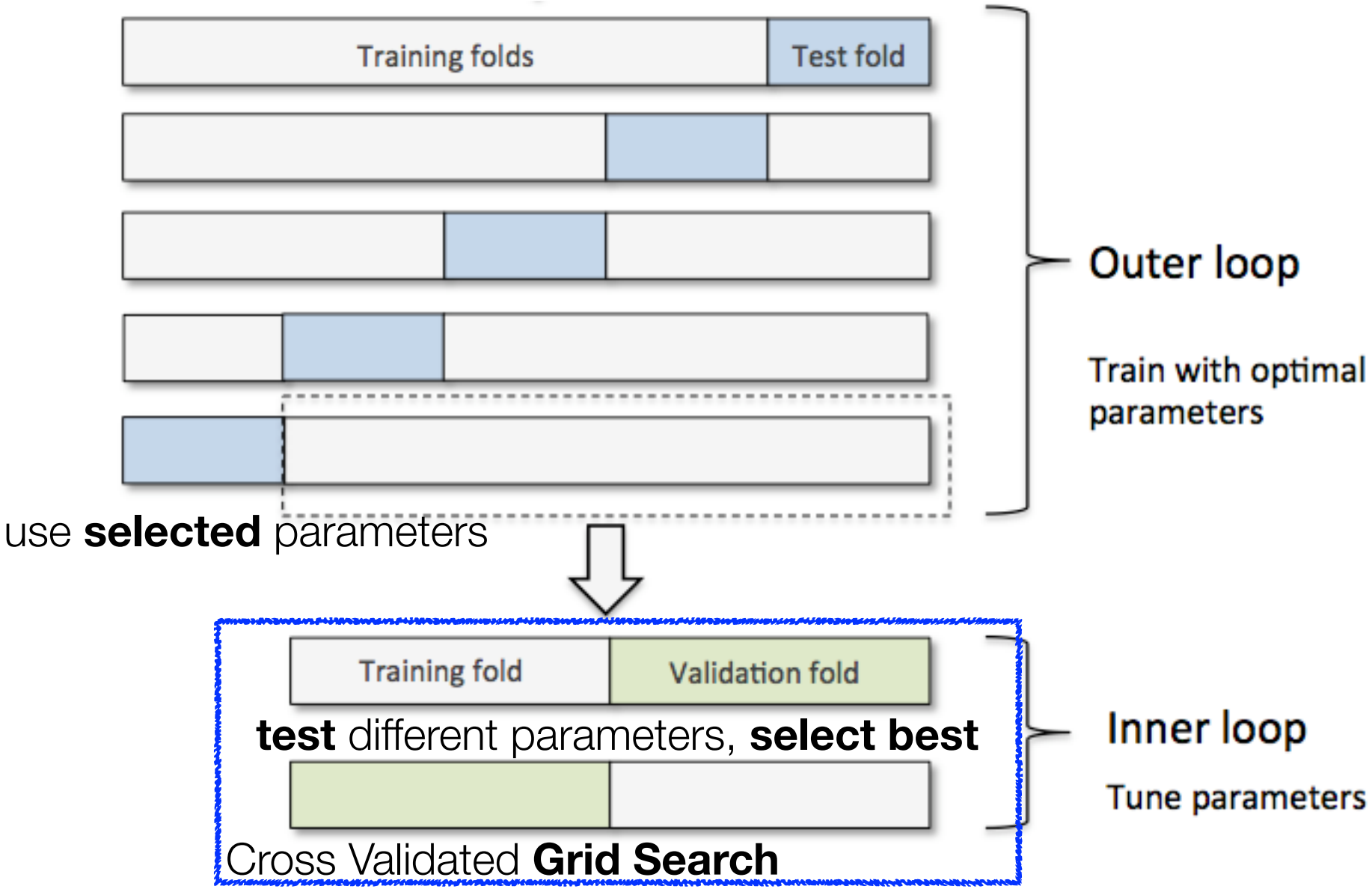
values, sampled

```
>>> from sklearn.datasets import load_iris
>>> from sklearn.linear_model import LogisticRegression
>>> from sklearn.model_selection import RandomizedSearchCV
>>> from scipy.stats import uniform
>>> iris = load_iris()
>>> logistic = LogisticRegression(solver='saga', tol=1e-2, max_iter=200,
...                               random_state=0)
>>> distributions = dict(C=uniform(loc=0, scale=4),
...                      penalty=['l2', 'l1'])
>>> clf = RandomizedSearchCV(logistic, distributions, random_state=0)
>>> search = clf.fit(iris.data, iris.target)
>>> search.best_params_
{'C': 2..., 'penalty': 'l1'}
```

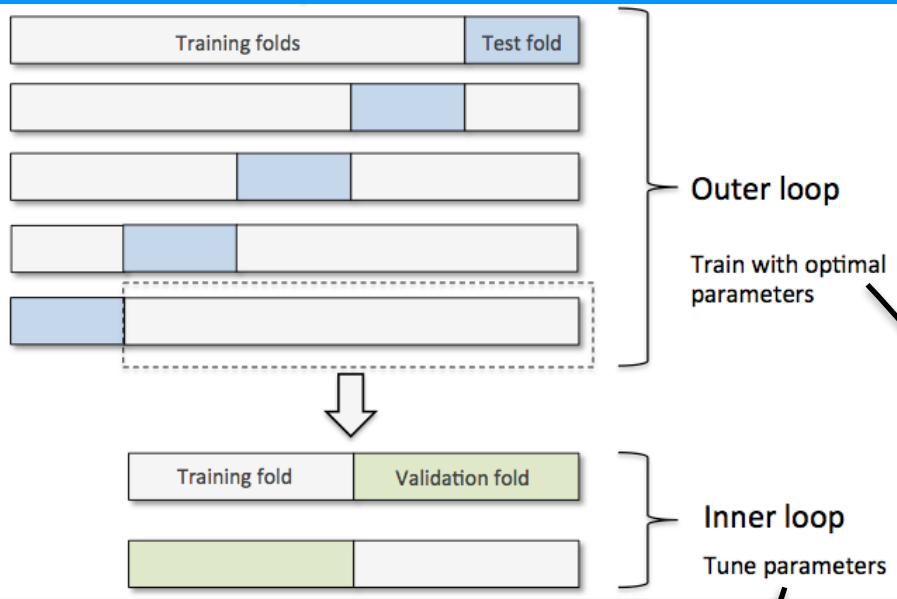
Review: Data Snooping

- Using the grid search parameters and testing on the same set…
  - the **performance on the dataset** could now be **biased**
  - cannot determine the **expected performance** on **new data**
  - this is **data snooping**

Review: Solution: Nested Cross Validation



Review: Nested Cross Validation: Hyper-parameters




```
gs = GridSearchCV(estimator=pipe_svc,
                  param_grid=param_grid,
                  scoring='accuracy',
                  cv=2)

# Note: Optionally, you could use cv=2
# in the GridSearchCV above to produce
# the 5 x 2 nested CV that is shown in the figure.

scores = cross_val_score(gs, X_train, y_train, scoring='accuracy', cv=5)
print('CV accuracy: %.3f +/- %.3f' % (np.mean(scores), np.std(scores)))
```

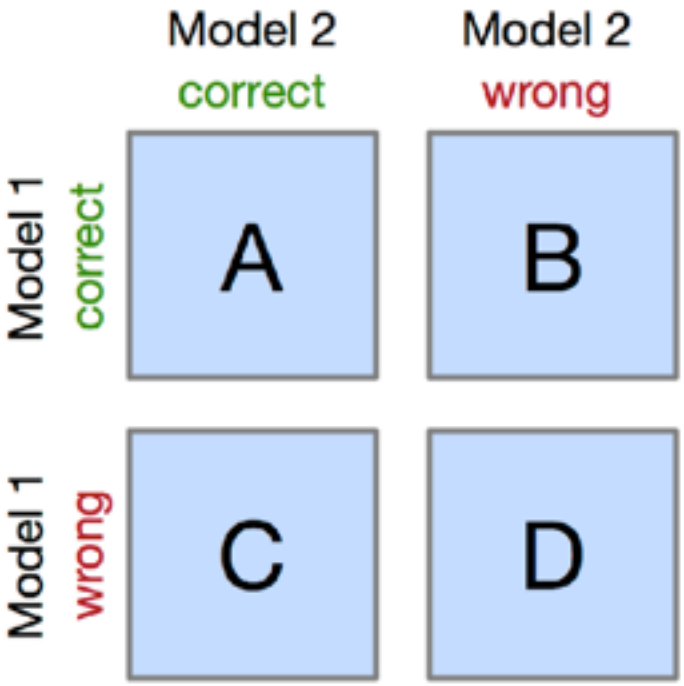
https://github.com/rasbt/python-machine-learning-book/

Self Test

- **What is the end goal of nested cross-validation?**
  - A. To determine hyper parameters
  - B. To estimate generalization performance
  - C. To estimate generalization performance when performing hyper parameter tuning
  - D. To estimate the variation in tuned hyper parameters

McNemar Testing for Comparing Performance

Few assumptions, **Null hypothesis**: predictions are not different!



McNemar and Edwards, 1948

$$\chi^2 \approx \frac{(|B - C| - 1)^2}{B + C}$$

If predictions are drawn from the same distributions, then this equation follows χ **squared statistic with one DOF**

Steps:

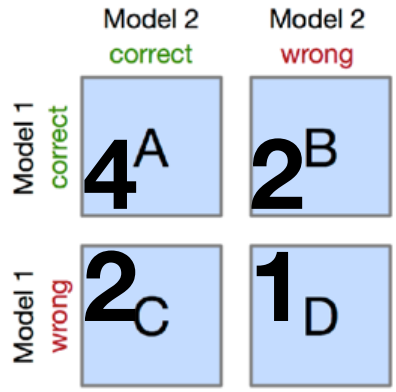
1. Compare each model's predictions on the same test data (2x2 matrix)
2. Calculate χ^2 statistic
3. Look up *critical value* associated with χ^2 statistic for given confidence
4. Are you confident enough to **reject the null hypothesis** that the performance is the same (p<0.05)?

One caveat: Statistical power depends upon B+C, which might be small, even with lots of test data.

https://sebastianraschka.com/blog/2018/model-evaluation-selection-part4.html

McNemar Example

Model 1	Model 2	Label	Matrix
T-shirt	T-shirt	T-shirt	A
Sneaker	T-shirt	Sneaker	B
T-shirt	Pullover	Pullover	C
Sneaker	Sneaker	Sneaker	A
T-shirt	Sneaker	Sneaker	C
Pullover	Pullover	T-shirt	D
Pullover	T-shirt	Pullover	B
Sneaker	Sneaker	Sneaker	A
Sneaker	Sneaker	Sneaker	A



McNemar and Edwards, 1948

$$\chi^2 \approx \frac{(|B - C| - 1)^2}{B + C}$$

$$\chi^2 = \frac{(|2 - 2| - 1)^2}{2 + 2} = 0.25$$

Confidence	0.90	0.95	0.99
1 DOF, Critical Value	2.706	3.841	6.635

https://www.itl.nist.gov/div898/handbook/eda/section3/eda3674.htm

Since 0.25 < 3.841, we cannot reject the null hypothesis. This means **we should not say the models' performance are different** based on the evidence.

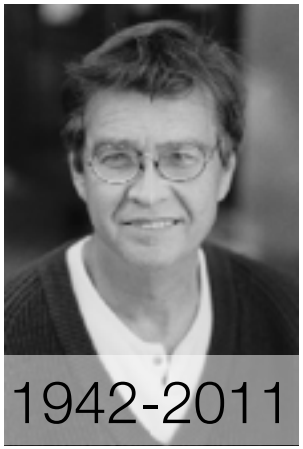
Town Hall

Some History of Deep Learning

Neural Networks: Where we left it

- Before 1986: AI Winter
- 1986: *Rumelhart*, *Hinton*, and *Williams* popularize gradient calculation for multi-layer network
  - *technically* introduced by Werbos in 1982
- **difference**: Rumelhart *et al.* validated ideas with a computer
- until this point no one could train a multiple layer network consistently
- algorithm is popularly called **Back-Propagation**
- wins pattern recognition prize in 1993, becomes de-facto machine learning algorithm in the 90's

David Rumelhart



1942-2011

Geoffrey Hinton

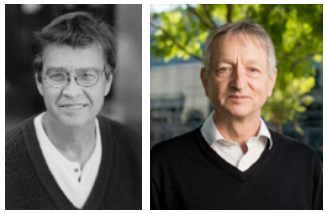
Machine Learning Timeline (Neural Nets)

- Up to this point: back propagation saved AI winter
- 80's, 90's, 2000's: neural networks for image processing start to get deeper
  - but back propagation no longer efficient for training
  - Back propagation gradient **stagnates** research—can't train **deeper** networks

- Second AI winter begins, research in NN plummets
- Funding for and accepted papers with Neural Networks asymptotically approaches zero

1949, Hebb's Law
Close neuron fire together

1960, Widrow & Hoff
Adaline Network



1986, Rumelhart & Hinton
Back-propagation

2003, Vapnik
Kernel SVMs

1940 — 1960 — 1980 — 2000 — 2020

Period of Discovery | First AI Winter | Golden Age of NN | 2nd AI Winter | Age of Deep Learning

1943, McCulloch & Pitts
Logic Gates of The Mind

1957, Rosenblatt
Perceptron

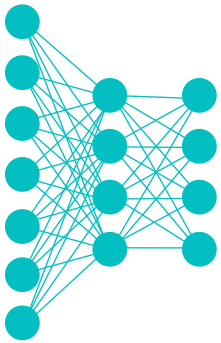
1969, Minsky & Papert
Linear Models are Doomed

2001, Breiman
Random Forests

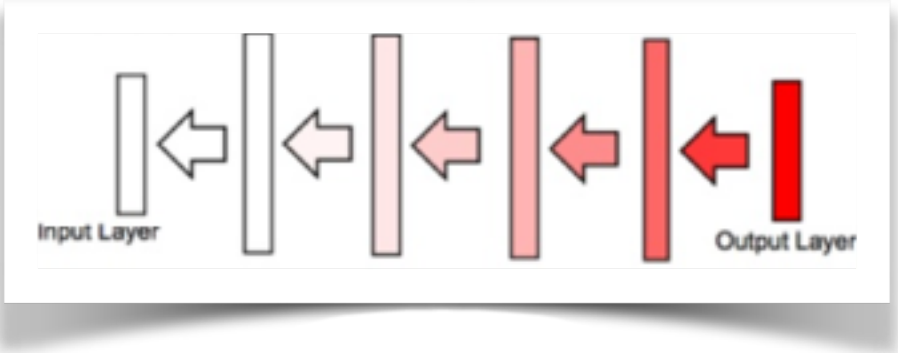
Read this: http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning/

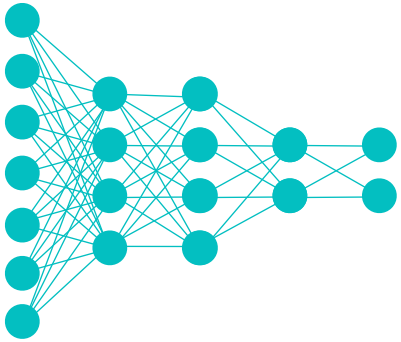
History of Deep Learning: Winter

- AI Winter is coming:



Easy to train, performs on par with other methods





Hard to train, performs worse than other methods
~chance (untrainable)

Researcher have difficulty reconciling expressiveness with performance

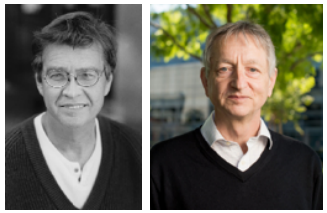
Read this: http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning/

Machine Learning Timeline (Neural Nets)

- 2004: Hinton secures funding from CIFAR based on his reputation
  - *eventually*: Canada would be savior for neural networks
  - Hinton rebrands: **Deep Learning**
- 2006: Hinton publishes paper on using pre-training and Restricted Boltzmann Machines
- 2007: Another paper: Deep networks are more efficient when pre-trained
  - RBMs not really the important part

1949, Hebb's Law
Close neuron fire together

1960, Widrow & Hoff
Adaline Network



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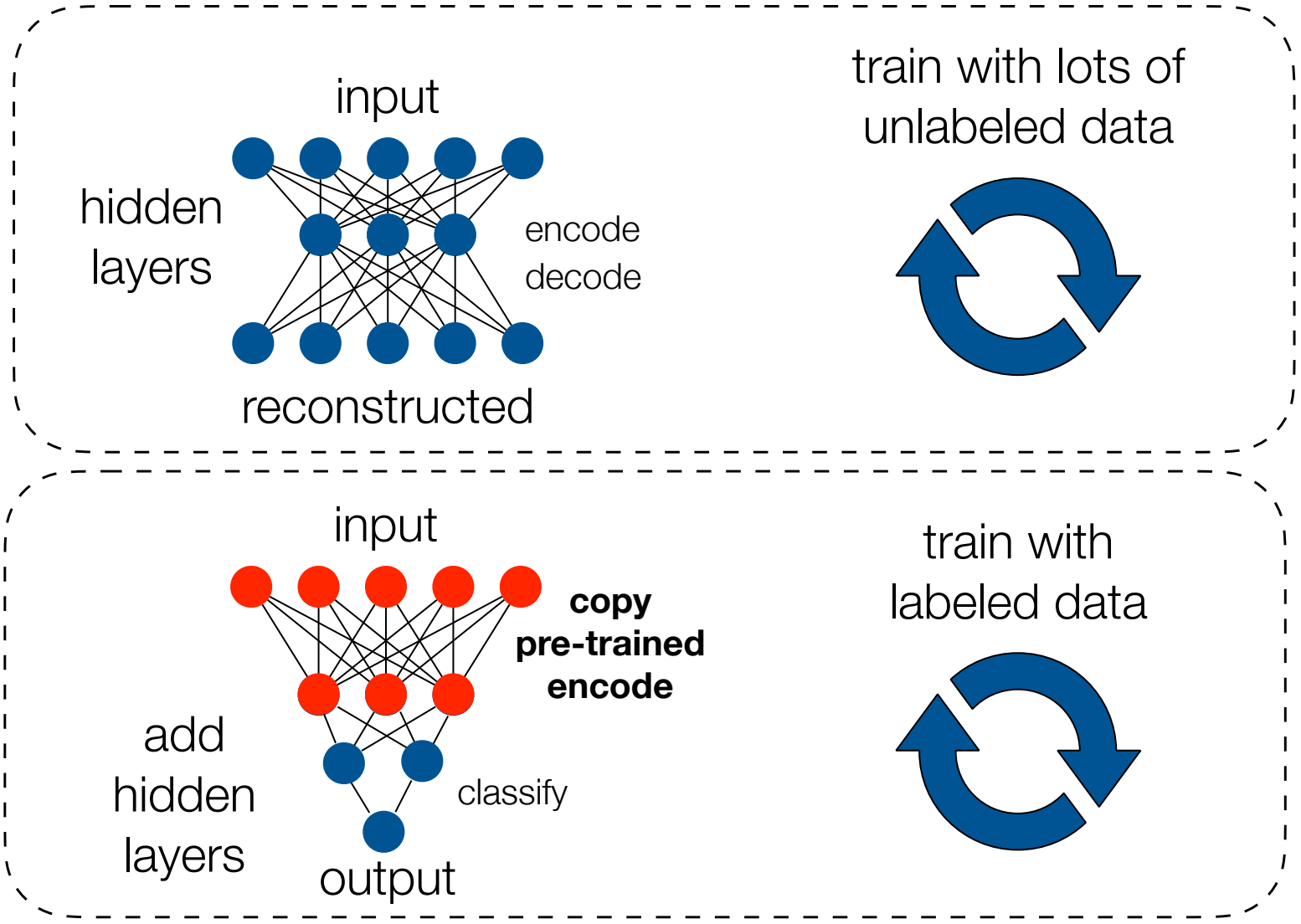
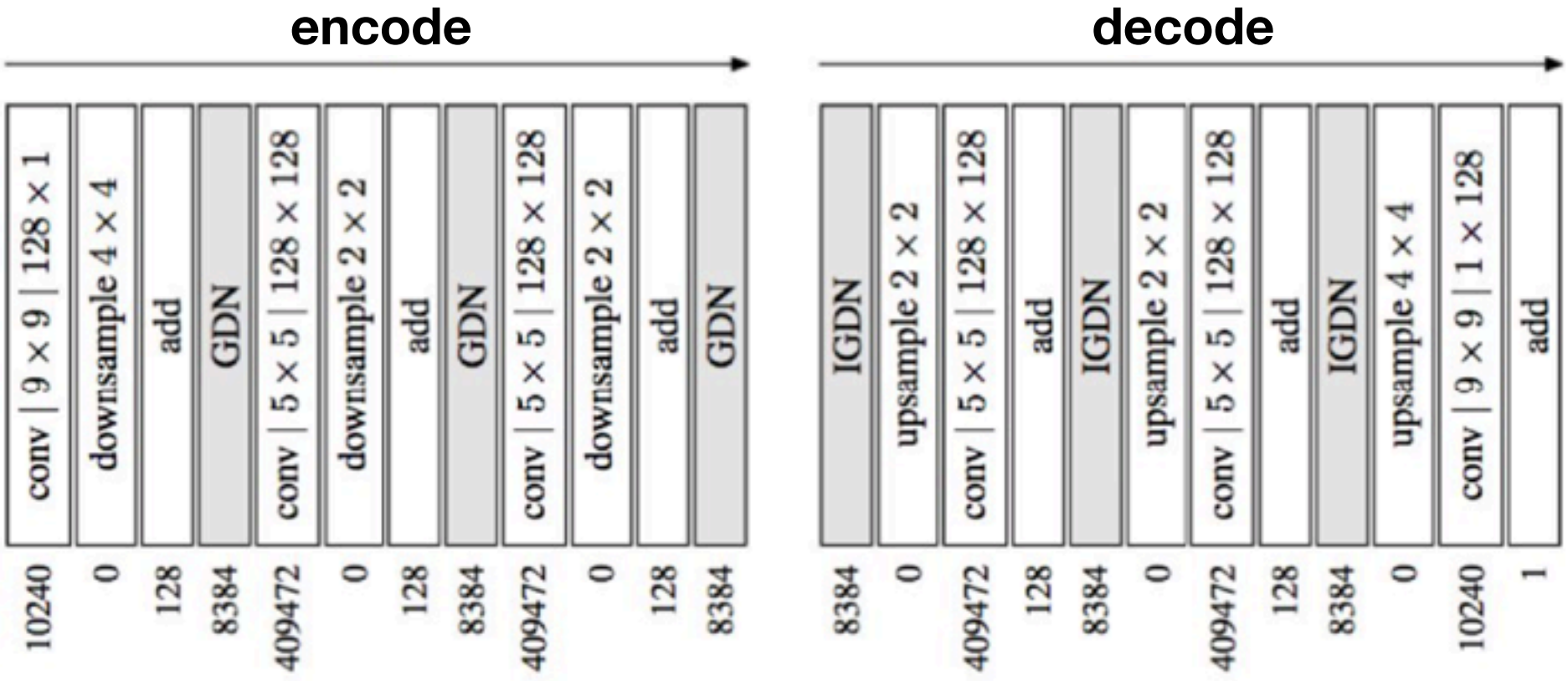
Pre-training: still in the long winter

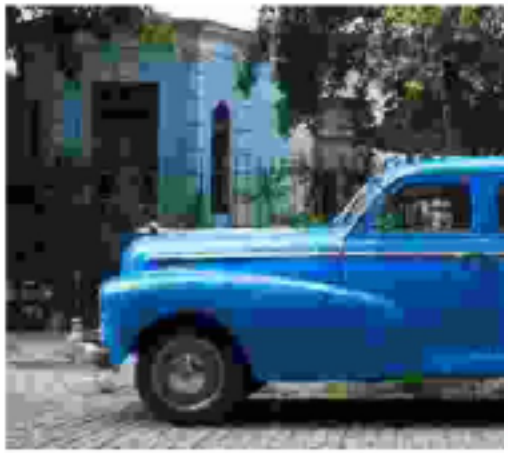
- auto-encoding (a form of pre-training)



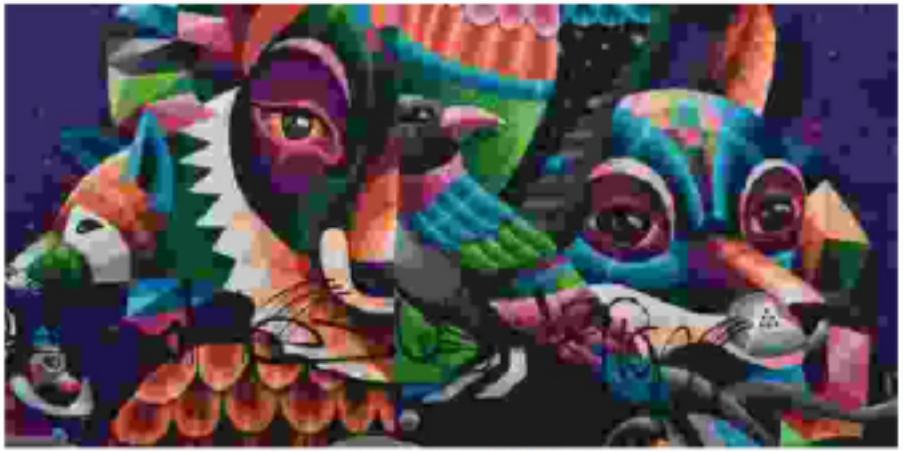
Pre-training: modern example



https://arxiv.org/abs/1611.01704



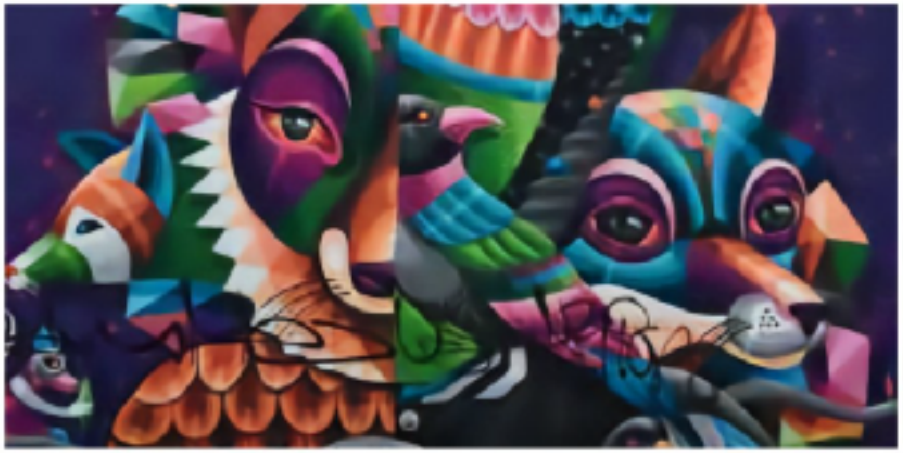
JPEG, 6006 bytes (0.170 bit/px), RMSE: 19.75



JPEG, 5928 bytes (0.168 bit/px), RMSE: 15.44/12.40, PSNR: 24.36 dB/26.26 dB

RMSE: 11.07/10.60, PSNR: 27.25 dB/27.63 dB

Proposed method, 5910 bytes (0.167 bit/px), RMSE



Proposed method, 5685 bytes (0.161 bit/px), RMSE: 10.41/5.98, PSNR: 27.78 dB/32.60 dB

it/px), RMSE: 6.10/5.09, PSNR: 32.43 dB/34.00 dB

JPEG 2000, 5918 bytes (0.167 bit/px), RMSE: 1

JPEG 2000, 5724 bytes (0.162 bit/px), RMSE: 13.75/7.02, PSNR: 25.36 dB/31.20 dB

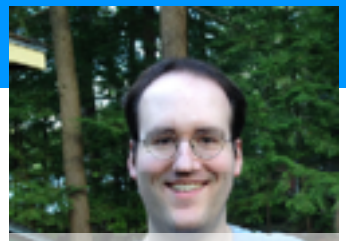
x), RMSE: 8.56/5.71, PSNR: 29.49 dB/32.99 dB

Still in the Long Winter

- 2009: Hinton's lab starts using GPUs, Also Andrew Ng
  - GPUs decrease training time by 70 fold…
- 2010: Hinton's and Ng's students go to internships with Microsoft, Google, IBM, and Facebook

Research at Google

Navdeep Jaitly
Google Brain Team



George Dahl
Google Brain Team

Abdel-rahman Mohamed
Microsoft Research
Redmond, Washington | Computer Software
Current Microsoft
Previous University of Toronto, IBM, Microsoft
Education University of Toronto

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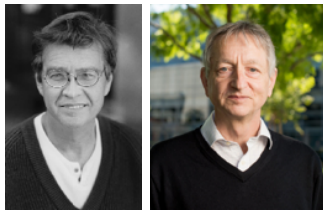

1986, Rumelhart & Hinton
Back-propagation

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- Xbox Voice
- Android Speech Recognition
- IBM Watson
- DeepFace
- All of Baidu

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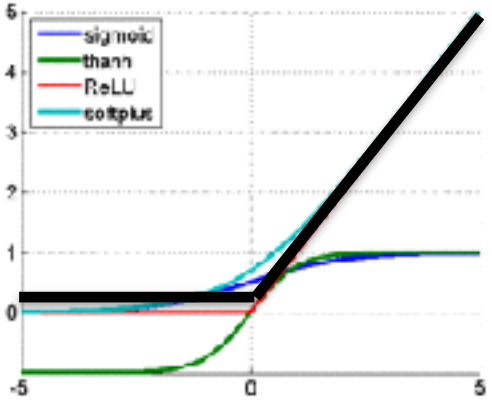
Read this: http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning/

Getting out of the long Winter

- 2011: Glorot and Bengio investigate more systematic methods for why past deep architectures did not work
  - **discover some interesting, simple fixes**: the type of neurons chosen and the selection of initial weights
  - do not require pre-training to get deep networks properly trained, just sparser representations and less complicated derivatives



ReLU: $f(x) = \max(0,x)$
$f'(x) = 1$ if $x>0$ else 0

1949, Hebb's Law
Close neuron fire together


1960, Widrow & Hoff
Adaline Network


1986, Rumelhart & Hinton
Back-propagation

2003, Vapnik
Kernel SVMs

1940 — 1960 — 1980 — 2000 — 2020

Period of Discovery | First AI Winter | Golden Age of NN | 2nd AI Winter | Age of Deep Learning

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Machine Learning Timeline (

- **ImageNet competition occurs**
- **Second place**: 26.2% error rate
- **First place**:
  - From Hinton's lab, uses convolutional network with ReLU and dropout
  - 15.2% error rate
- Computer vision adopts deep learning with convolutional neural networks en mass

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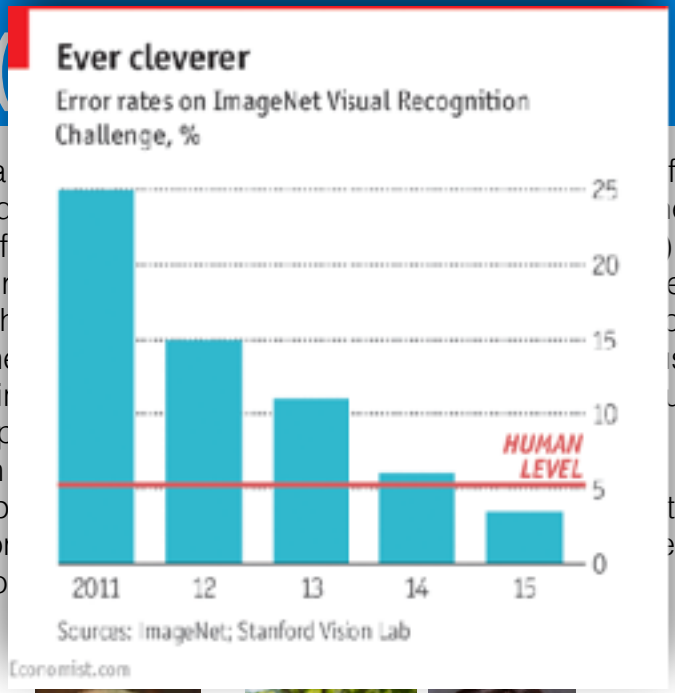

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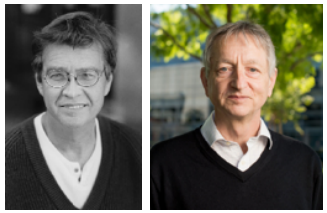

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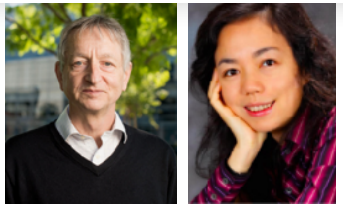

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CNNs win ImageNet

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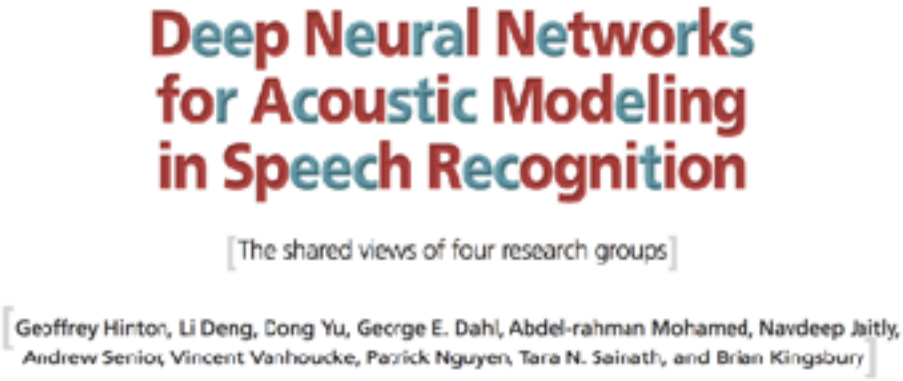
Machine Learning Timeline (Neural Nets)

- 2012: Hinton Lab, Google, IBM, and Microsoft jointly publish paper, popularity for deep learning methods increases



https://www.cs.toronto.edu/~gdahl/papers/deepSpeechReviewSPM2012.pdf

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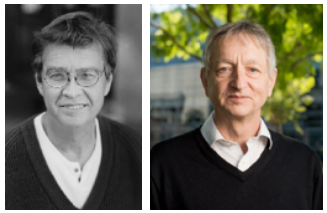

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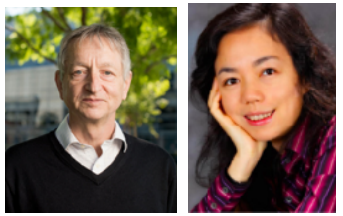

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Machine Learning Timeline (Neural Nets)

- 2013: Andrew Ng and Google (BrainTeam)
  - run unsupervised feature creation on YouTube videos (becomes computer vision benchmark)

The work resulted in unsupervised neural net learning of an unprecedented scale - 16,000 CPU cores powering the learning of a whopping 1 billion weights. The neural net was trained on Youtube videos, entirely without labels, and learned to recognize the most common objects in those videos.

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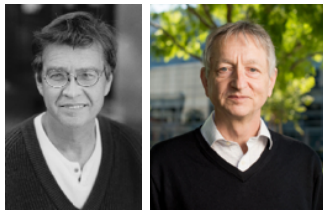

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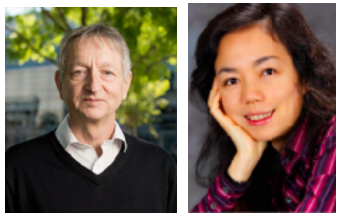

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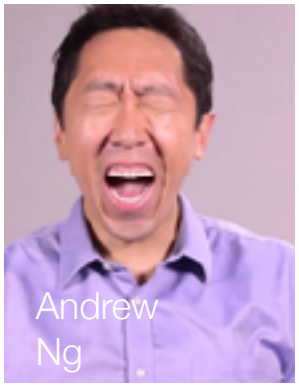
A summary of the Deep Learning people:

Stayed at Univ. Montreal
Advises IBM

Heads Facebook AI Team

Univ. Toronto
Google

Stanford (HAI)
Former Chief Scien., AI/MLGoogle Cloud



Coursera
Baidu
Google

Stanford
Founded Coursera
MacArthur Genius

- Hinton: Restricted Boltzmann Machine, Deep autoencoder
- Bengioc neural language modeling.
- LeCun: Convolutional Neural Network
- NIPS, ICML, CVPR, ACL
- Google Brain, Deep Mind.
- FaceBook AI.

Made Deep Learning Instruction Accessible

deep learning

doi:10.1038/nature14539

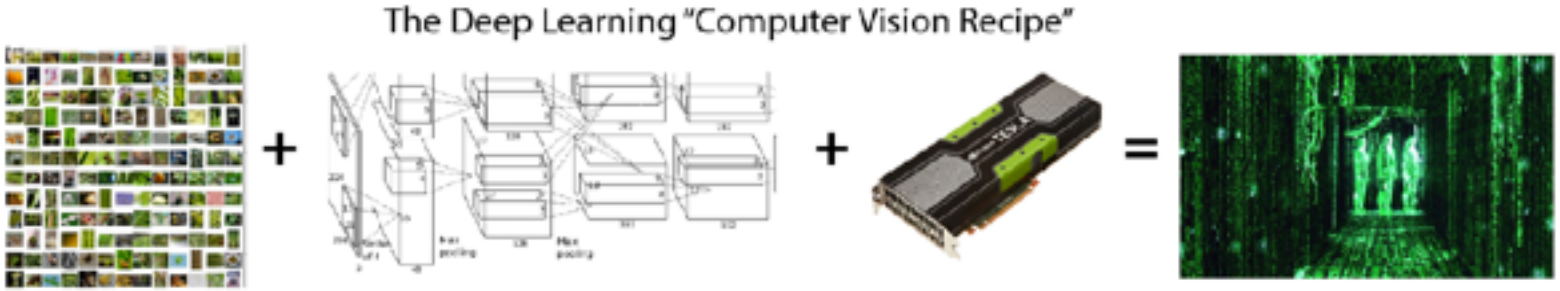
ning

Geoffrey Hinton[4,5]

Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection and many other domains such as drug discovery and genomics. Deep learning discovers intricate structure in large data sets by using the backpropagation algorithm to indicate how a machine should change its internal parameters that are used to compute the representation in each layer from the representation in the previous layer. Deep convolutional nets have brought about breakthroughs in processing images, video, speech and

History of Deep Learning

- **Hinton** summarized what we learned in deep learning from the 2006 to present. Where we went wrong before present day:
  - labeled dataset were 1000s of times too small
  - computers were millions of times too slow
  - weights were initialized in stupid ways
  - we used the wrong non-linearities
- Or **Larson's Laws**:
  - use a GPU when possible, init weights for consistent gradient magnitude, ReLU/SiLU where it makes sense (like in early feedforward layers), clip the gradient magnitude, and use adaptive learning to learn more quickly!



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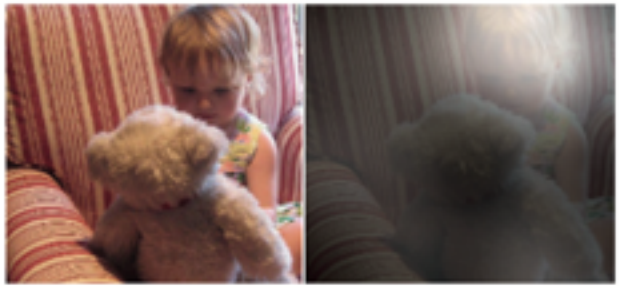
Famous examples:

A woman is throwing a **frisbee** in a park.

A **dog** is standing on a hardwood floor.

A **stop** sign is on a road with a mountain in the background

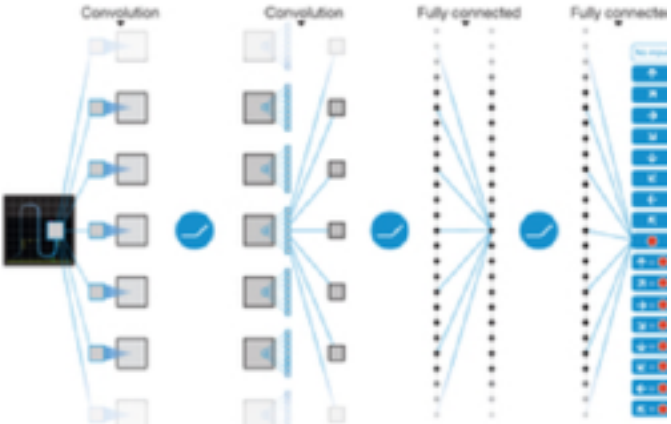


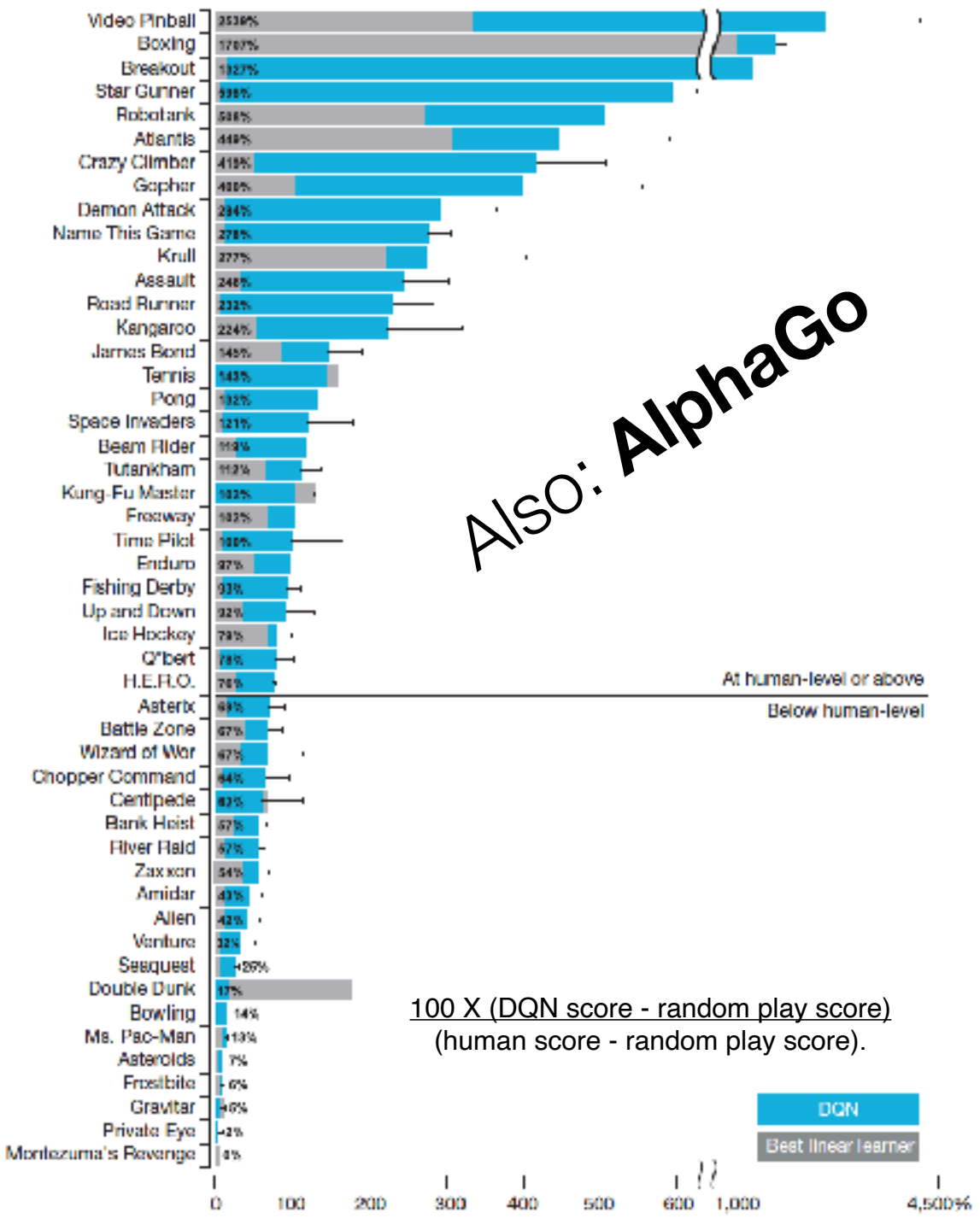
A little **girl** sitting on a bed with a teddy bear.

A group of **people** sitting on a boat in the water.

A giraffe standing in a forest with **trees** in the background.

More Famous





Also: **AlphaGo**

Credit for Deep Learning

Official ACM @TheOfficialACM

Yoshua Bengio, Geoffrey Hinton and Yann LeCun, the fathers of #DeepLearning, receive the 2018 #ACMTuringAward for conceptual and engineering breakthroughs that have made deep neural networks a critical component of computing today. bit.ly/2HVJtdV

Machine learning is the science of credit assignment. The machine learning community itself profits from proper credit assignment to its members. The inventor of an important method should get credit for inventing it. She may not always be the one who popularizes it. Then the popularizer should get credit for popularizing it (but not for inventing it). Relatively young research areas such

Review of Deep Learning History

- Up to this point: back propagation saved AI winter for NN (Hinton and others!)
- 80's, 90's, 2000's: convolutional networks for image processing start to get deeper
  - but back propagation no longer does great job at training them
- SVMs and Random Forests gain traction…
  - The second AI winter begins, research in NN plummets
- 2004: Hinton secures funding from CIFAR in 2004 Hinton rebrands: Deep Learning
- 2006: Auto-encoding and Restricted Boltzmann Machines
- 2007: Deep networks are more efficient when pre-trained
- 2009: GPUs decrease training time by 70 fold…
- 2010: Hinton's students go to internships with Microsoft, Google, and IBM, making their speech recognition systems faster, more accurate and deployed in only 3 months…
- 2012: Hinton Lab, Google, IBM, and Microsoft jointly publish paper, popularity sky-rockets for deep learning methods
- 2011-2013: Ng and Google run unsupervised feature creation on YouTube videos (becomes computer vision benchmark)
- 2012+: Pre-training is not actually needed, just solutions for vanishing gradients (like ReLU, SiLU, initializations, more data, GPUs)

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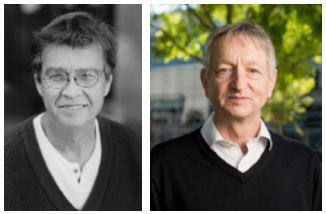

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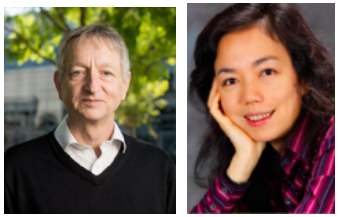

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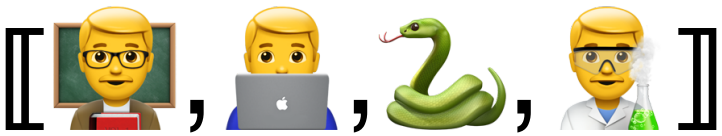
2015, Google
Tensorflow Open Source

End of Session

- Next Time:
  - Introduction to TensorFlow
  - Wide and Deep Networks

Lecture Notes for

Machine Learning in Python



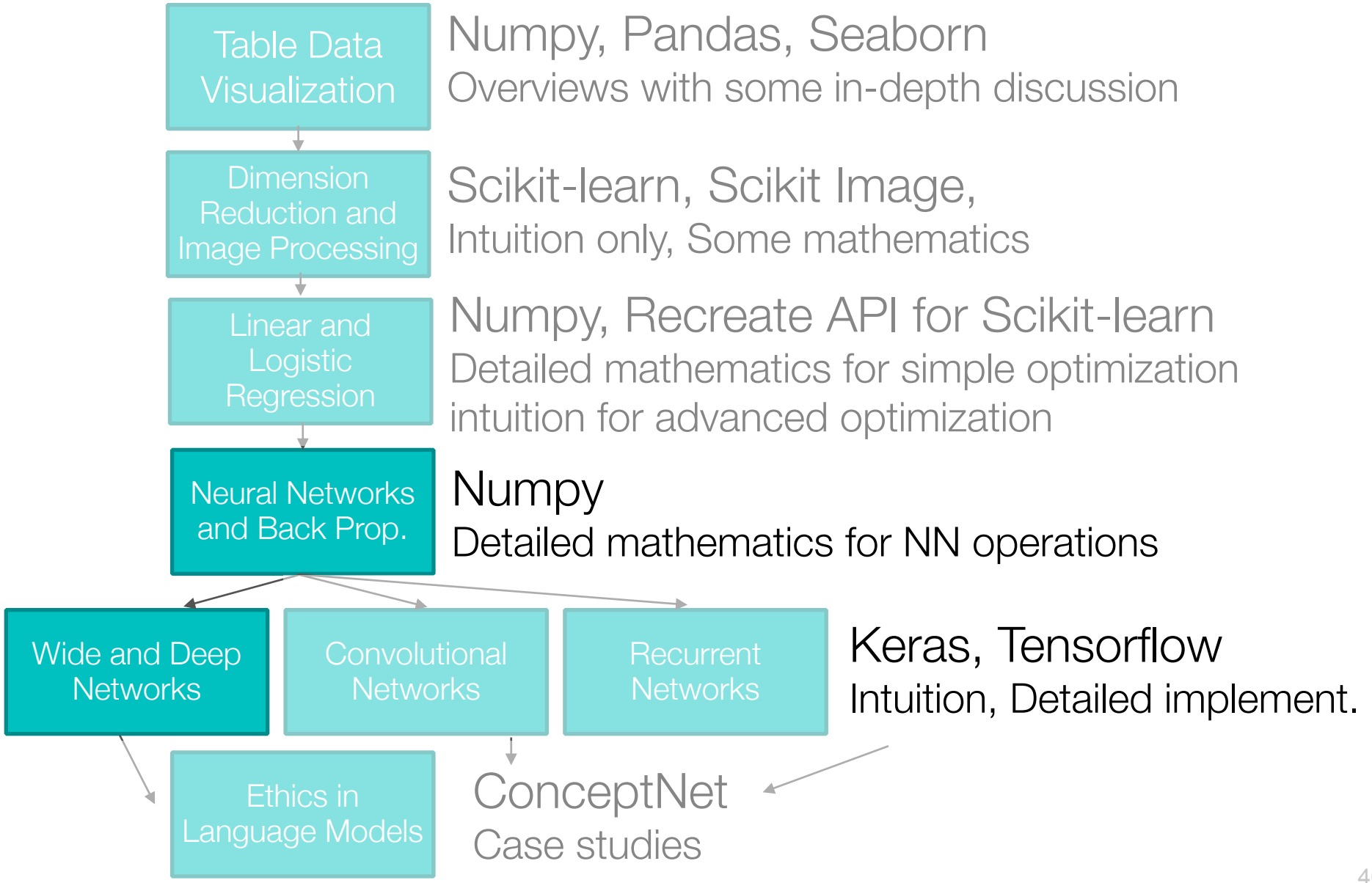
Professor Eric Larson

Keras: Wide and Deep Networks

Lecture Agenda

- Logistics:
  - CS 8321 in Spring
  - Grading and lab deadlines
- Get out of the long winter…
- Introduction to TensorFlow
  - Tensors, Namespaces, Numerical methods
  - Deep APIs
- Wide and Deep Networks

Class Overview, by topic



Last Time

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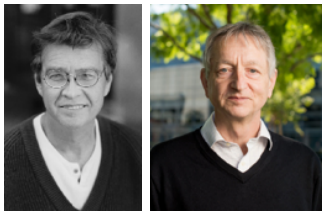

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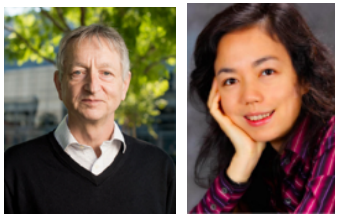

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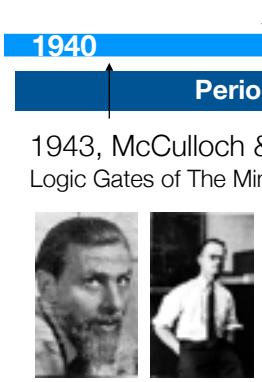

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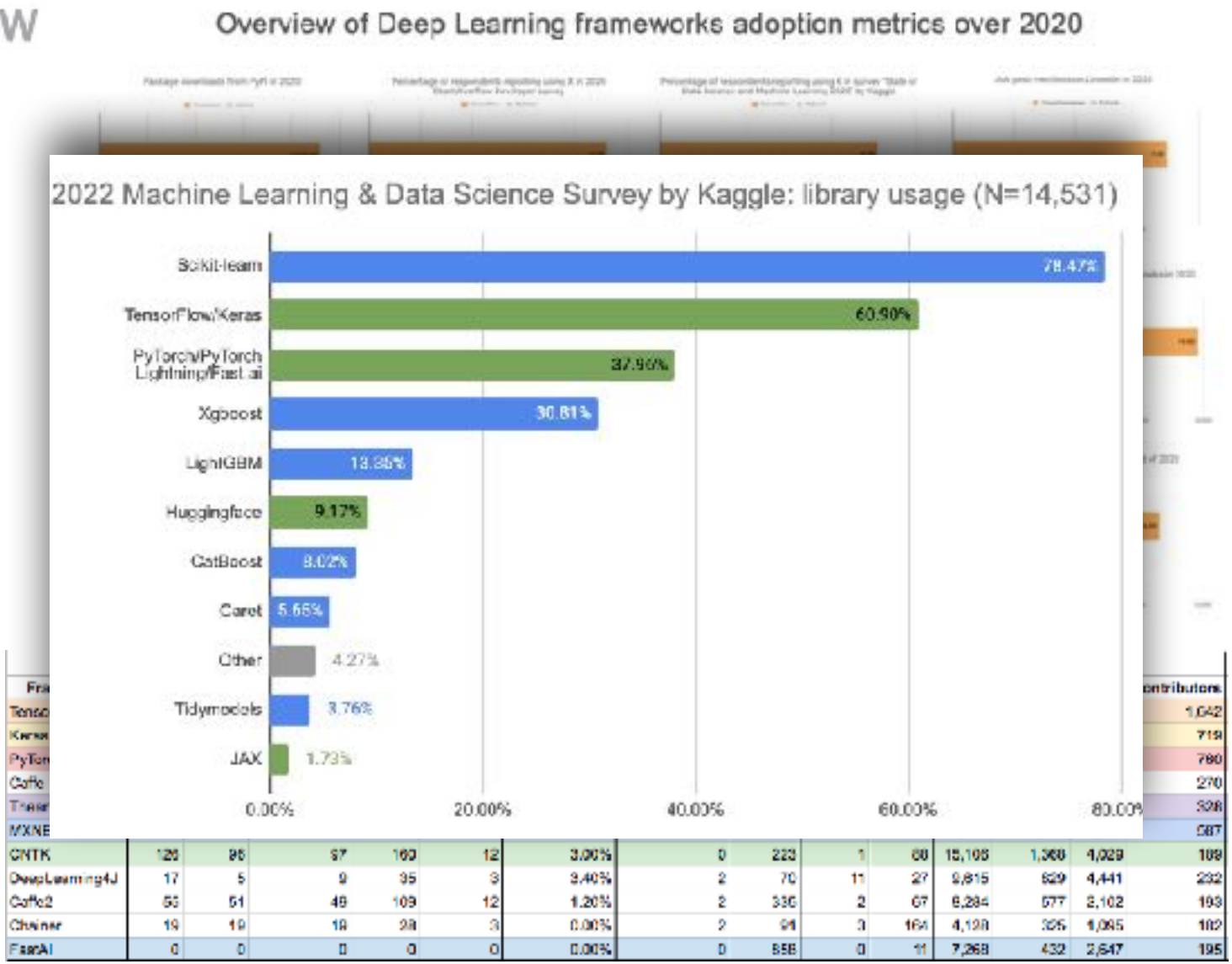
TensorFlow

"Further discussion of it merely incumbers the literature and befogs the mind of fellow students."

- 2007: NIPS program committee rejects a paper on deep learning by *al. et.* Hinton because they already accepted a paper on deep learning and two papers on the same topic would be excessive.
- ~2009: A reviewer tells Yoshua Bengio that papers about neural nets have no place in ICML.
- ~2010: A CVPR reviewer rejects Yann LeCun's paper even though it beats the state-of-the-art. The reviewer says that it tells us nothing about computer vision because everything is learned.

Options for Deep Learning Toolkits

1. TensorFlow
2. Keras
3. PyTorch
4. Caffe
5. theano
6. mxnet
7. CNTK
8. DL4J
9. Caffe2
10. Chainer
11. fast.ai



CNTK	126	95	97	169	12	3.00%	0	223	1	69	15,105	1,360	4,029	169
DeepLearning4J	17	5	9	35	3	9.40%	2	70	11	27	2,815	529	4,441	232
Caffe2	55	51	49	109	12	1.20%	2	330	2	67	6,284	577	2,102	193
Chainer	19	19	19	28	3	0.00%	2	91	3	164	4,139	325	1,085	102
FastAI	0	0	0	0	0	0.00%	0	558	0	11	7,268	432	2,647	195

Tensorflow

- Open sourced library from Google
- Second generation release from Google Brain
  - supported for Linux, Unix, Windows
  - Also works on Android/iOS
- Released November 9th, 2015
  - (this class first offered January 2016)

Programmatic creation

- Most toolkits use python to build a **computation graph** of operations
  - Build up computations
  - Execute computations
- **Most Toolkits Support:**
  - tensor creation
  - functions on tensors
  - automatic differentiation

- Tensors are just multidimensional arrays
  - like in Numpy
    - scalars (biases and constants)
    - vectors (e.g., input arrays)
    - 2D matrices (e.g., images)
    - 3D matrices (e.g., color images)
    - 4D matrices (e.g., batches of color images)

Tensor basic functions

- Easy to define operations on tensors

```
a = tf.constant(5.0)

b = tf.constant(6.0)

c = a * b
```

Numpy	TensorFlow
`a = np.zeros((2,2)); b = np.ones((2,2))`	`a = tf.zeros((2,2)), b = tf.ones((2,2))`
`np.sum(b, axis=1)`	`tf.reduce_sum(a,reduction_indices=[1])`
`a.shape`	`a.get_shape()`
`np.reshape(a, (1,4))`	`tf.reshape(a, (1,4))`
`b * 5 + 1`	`b * 5 + 1`
`np.dot(a,b)`	`tf.matmul(a, b)`
`a[0,0], a[:,0], a[0,:]`	`a[0,0], a[:,0], a[0,:]`

Also supports convolution: `tf.nn.conv2d, tf.nn.conv3D`

https://cs224d.stanford.edu/lectures/CS224d-Lecture7.pdf

Tensor neural network functions

- Easy to define operations on layers of networks

```
• relu(features, name=None)
• bias_add(value, bias, data_format=None, name=None)
• sigmoid(x, name=None)
• tanh(x, name=None)
• conv2d(input, filter, strides, padding)
• conv1d(value, filters, stride, padding)
• conv3d(input, filter, strides, padding)
• conv3d_transpose(value, filter, output_shape, strides)
• sigmoid_cross_entropy_with_logits(logits, targets)
• softmax(logits, dim=-1)
• log_softmax(logits, dim=-1)
• softmax_cross_entropy_with_logits(logits, labels, dim=-1)
```

- Each function created *knows its gradient*
- **Automatic Differentiation** is just **chain rule**
- But… lets start simple…

Tensor function evaluation

```
import tensorflow as tf

a = tf.constant(5.0)
b = tf.constant(6.0)

c = a*b

with tf.Session() as sess:
    print(sess.run(c))
    print(c.eval())
```

output = 30

- Easy to define operations on tensors
  - constant
  - variables
  - placeholders
- Nothing evaluated until you define a session and tell it to evaluate it
- Session defines configuration of execution
  - like GPU versus CPU

https://cs224d.stanford.edu/lectures/CS224d-Lecture7.pdf

Computation Graph with Code

```
import tensorflow as tf
X = tf.Placeholder()
y = tf.Placeholder()
```

$$J(\mathbf{W}) = \frac{1}{N}\sum_{i}^{N}(y^{(i)} - \underbrace{(\mathbf{W}\cdot\mathbf{x}^{(i)} + \mathbf{b})}_{y_{pred}})^2$$

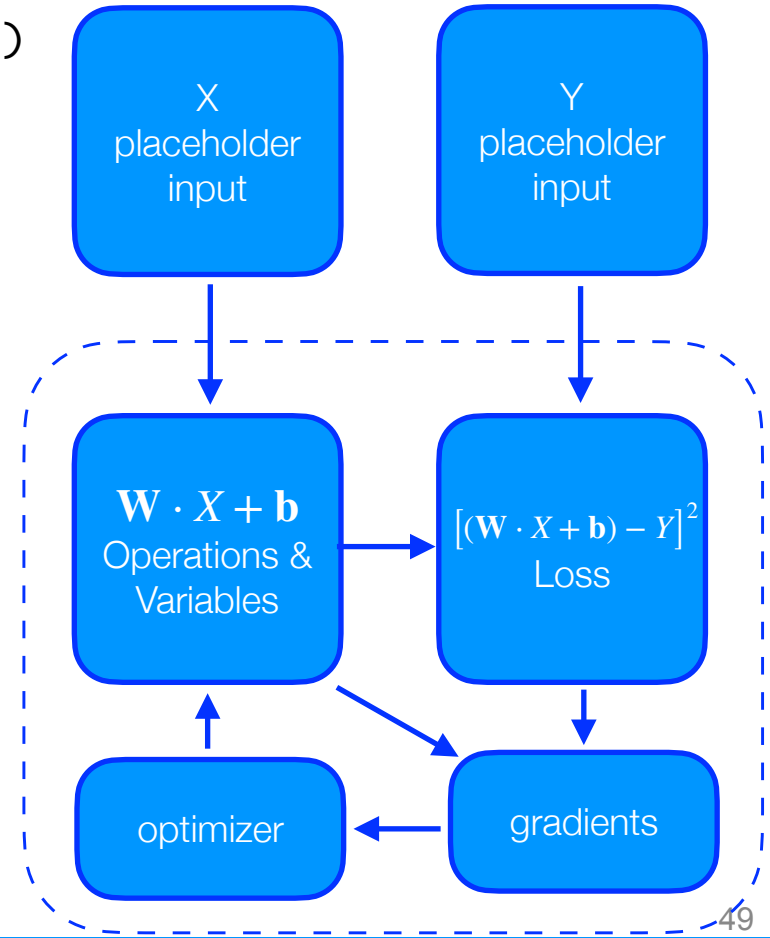
1. **Setup** Variables and computations

```
W = tf.Variable("weights", (1,num_features),
        initializer=tf.random_normal_initializer())
b = tf.Variable("bias", (1,),
        initializer=tf.constant_initializer(0.0))

y_pred = tf.matmul(X,W) + b
loss = tf.reduce_sum((y-y_pred)**2)/n_samples
```

2. Add **optimization** operation to computation graph
   Adjusts variables (W, b) to minimize loss with automatic differentiation

```
opt = tf.train.AdamOptimizer()
opt_operation = opt.minimize(loss)

with tf.Session() as sess:
    sess.run(tf.initialize_all_variables())
    sess.run([opt_operation],
        feed_dict={X:X_numpy, y: y_numpy})
```

3. **Run graph operation** once, → one optimization update on all variables



http://www.datasciencecentral.com/profiles/blogs/google-open-source-tensorflow

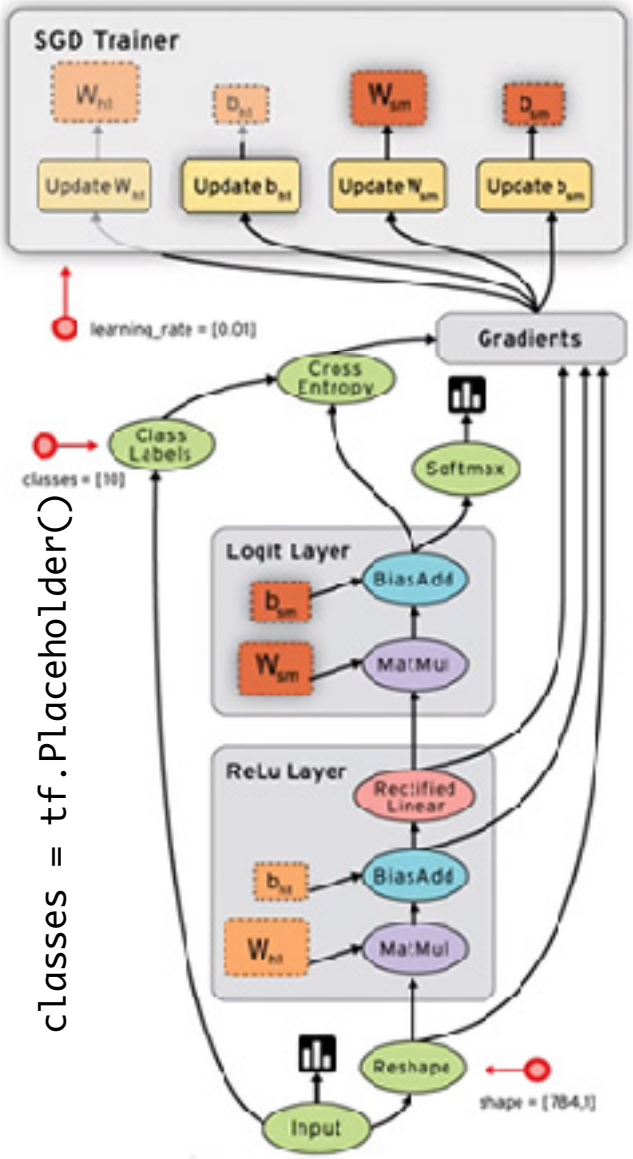
Tensorflow Mini-batching

```
opt = tf.train.AdamOptimizer()
opt_operation = opt.minimize(loss)

with tf.Session() as sess:
    sess.run(tf.initialize_all_variables())
    sess.run([opt_operation], feed_dict={X:X_numpy, y: y_numpy})

    for _ in range(500):
        indices = np.random.choice(n_samples, batch_size)
        X_batch, y_batch = X_numpy[indices], y_numpy[indices]

        _, loss_val = sess.run([opt_operation, loss],
                               feed_dict={X:X_batch, y:y_batch})
```

- Example shown is **graph execution**
  - Build up computations and Execute computations when instructed
  - Makes it sometimes **hard to debug** but its **fast**
- Alternative: **eager execution** (we won't cover this)

https://cs224d.stanford.edu/lectures/CS224d-Lecture7.pdf

Computation Graph, Two Layer Network




```
opt = tf.train.SGDOptimizer(learning_rate=0.01)
opt_operation = opt.minimize(loss)
```

```
A_hl = tf.relu( tf.matmul(Input,W_hl) + b_hl )
A_sm = tf.matmul(A_hl,W_sm) + b_sm

y_pr = tf.softmax(A_sm)
loss = tf.sparse_softmax_cross_entropy_with_logits(
                classes, A_sm )
```

```
W_sm = tf.Variable(…)
b_sm = tf.Variable(…)
W_hl = tf.Variable(…)
b_hl = tf.Variable(…)
```

```
Input = tf.Placeholder() # size is 28x28
Input = tf.Reshape(Input, [784,1])
```

http://www.datasciencecentral.com/profiles/blogs/google-open-source-tensorflow

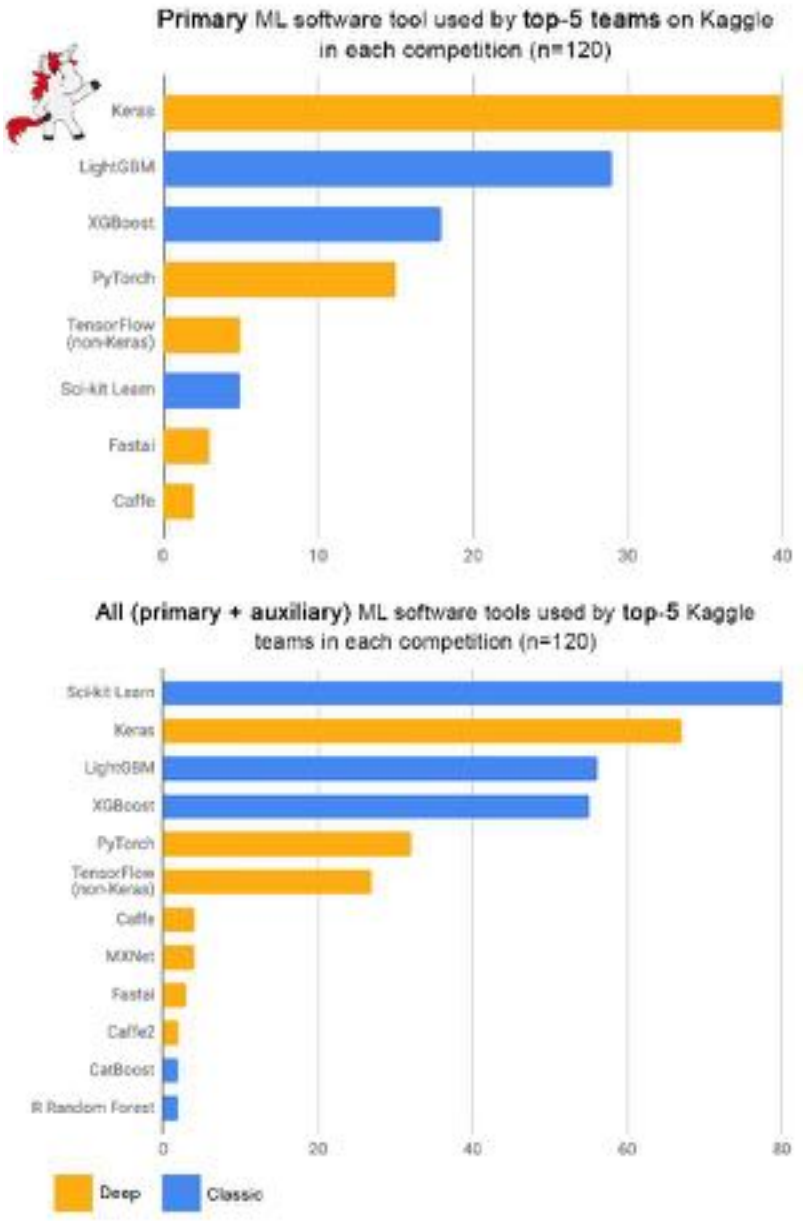
Tensorflow Simplification

- **Self Test**: Can the syntax be simplified?
  - (A) **Yes**, we could write a generic mini-batch optimization computation graph, then use it for arbitrary inputs
  - (B) **Yes**, but we lose control over the optimization procedures
  - (C) **Yes**, but we lose control over the NN models that we can create via Tensorflow
  - (D) **None of the above**

Keras Programming Interfaces

- **Keras Sequential API**
  - great for simple, feed forward models
- **Keras Functional API**
  - build models through series of nested functions
  - each “function” represents an operation in the NN
- **Keras Classes (Inheritance)**
  - good for more advanced functionality

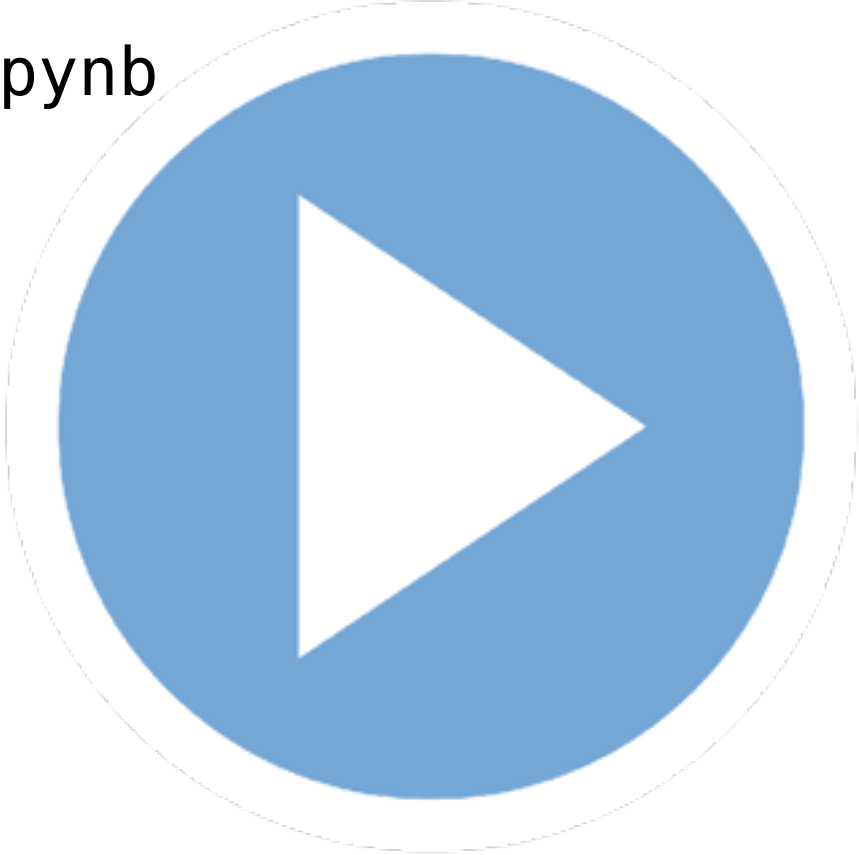
```
from tensorflow import keras
```



Demo

`10. Keras Wide and Deep.ipynb`

Reinventing the MLP Wheel



Make me slow down if I go too fast!!

Categorical Feature Embeddings

- One hot encoded data can be made dense through a matrix multiplication

Trainable Matrix in Network

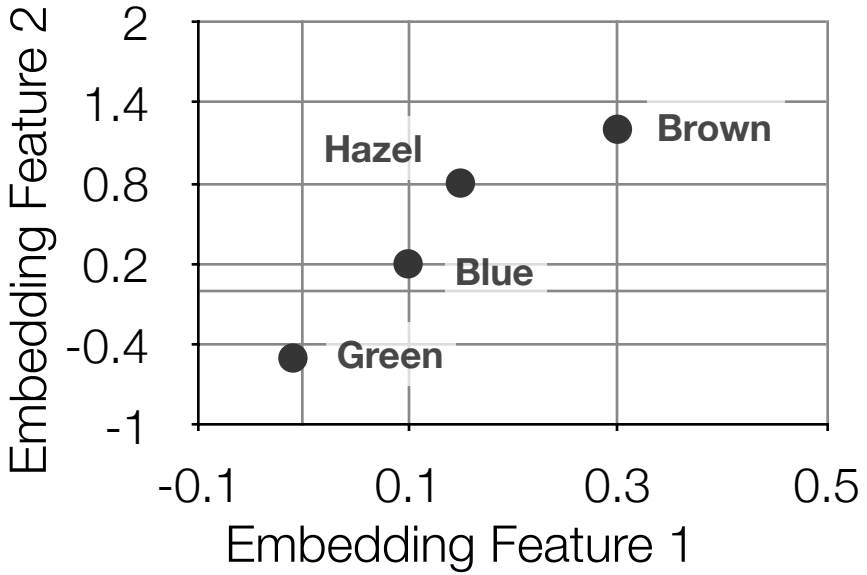
Reduced Dimensions

0.1	0.3	-0.01	0.15
0.2	1.2	-0.5	0.8

Num Categories

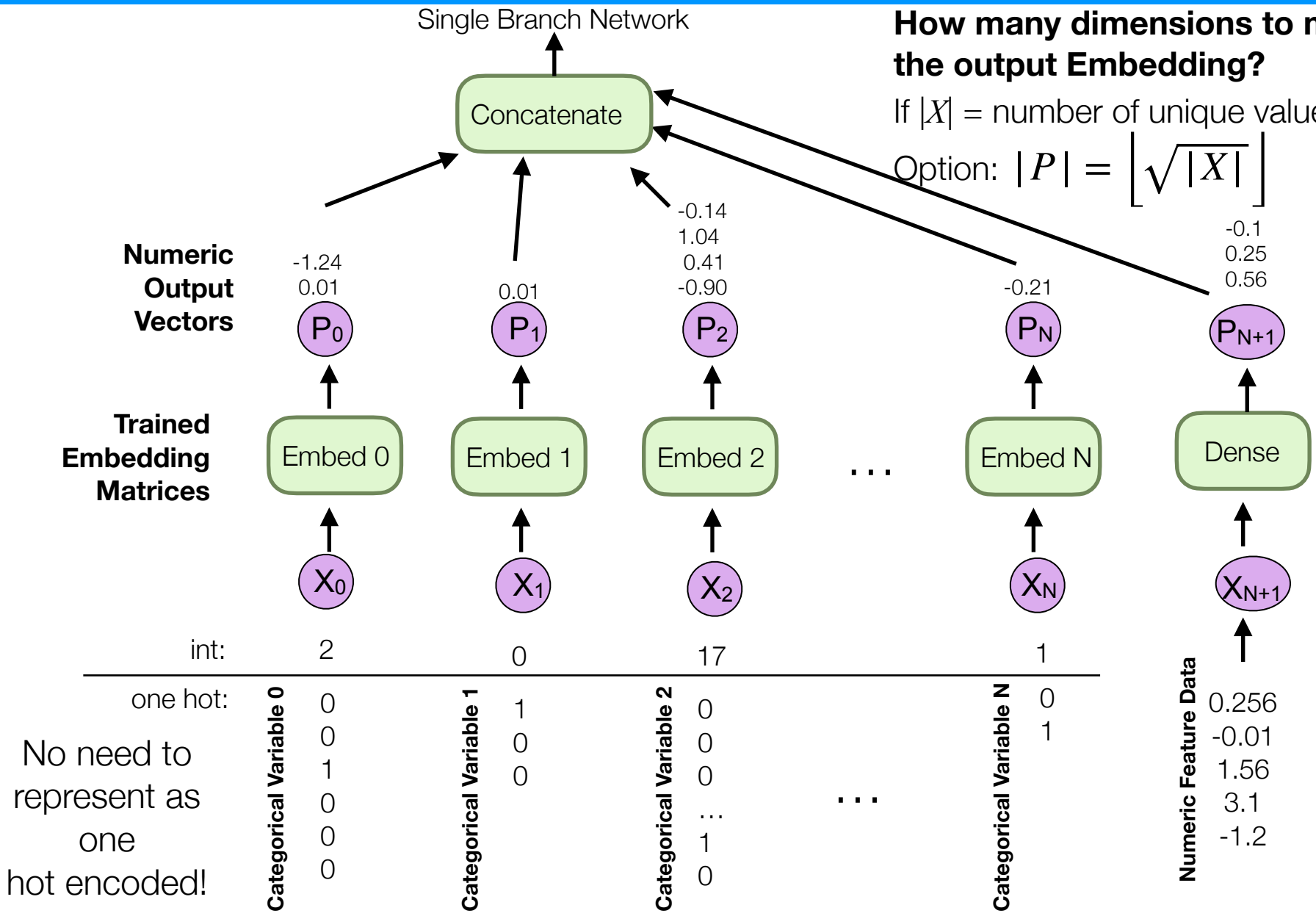
Eye Color

$$\begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \begin{matrix} \text{Blue} \rightarrow 0 \\ \text{Brown} \rightarrow 1 \\ \text{Green} \rightarrow 2 \\ \text{Hazel} \rightarrow 3 \end{matrix}$$



Computationally: there is no need to one hot encode eye color, we can just use the integer to index into the **embedding matrix**

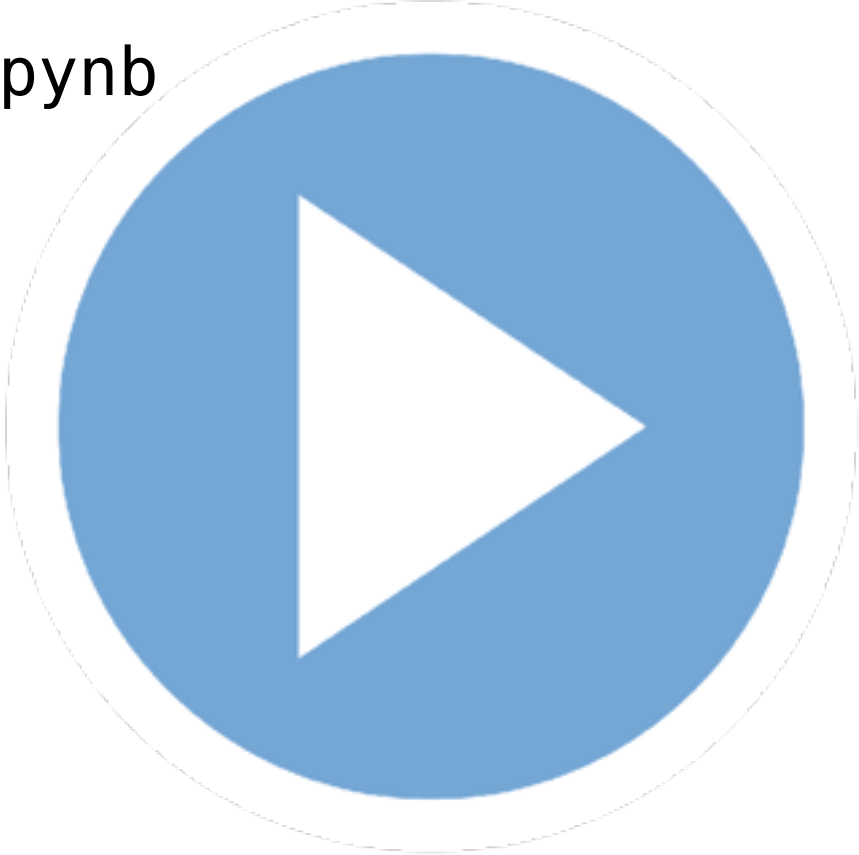
Using Embeddings in Keras



"Finish" Demo

`10. Keras Wide and Deep.ipynb`

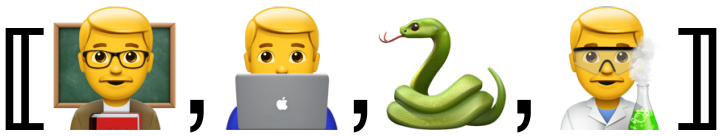
Reinventing the MLP Wheel



Make me slow down if I go too fast!!

Lecture Notes for

Machine Learning in Python



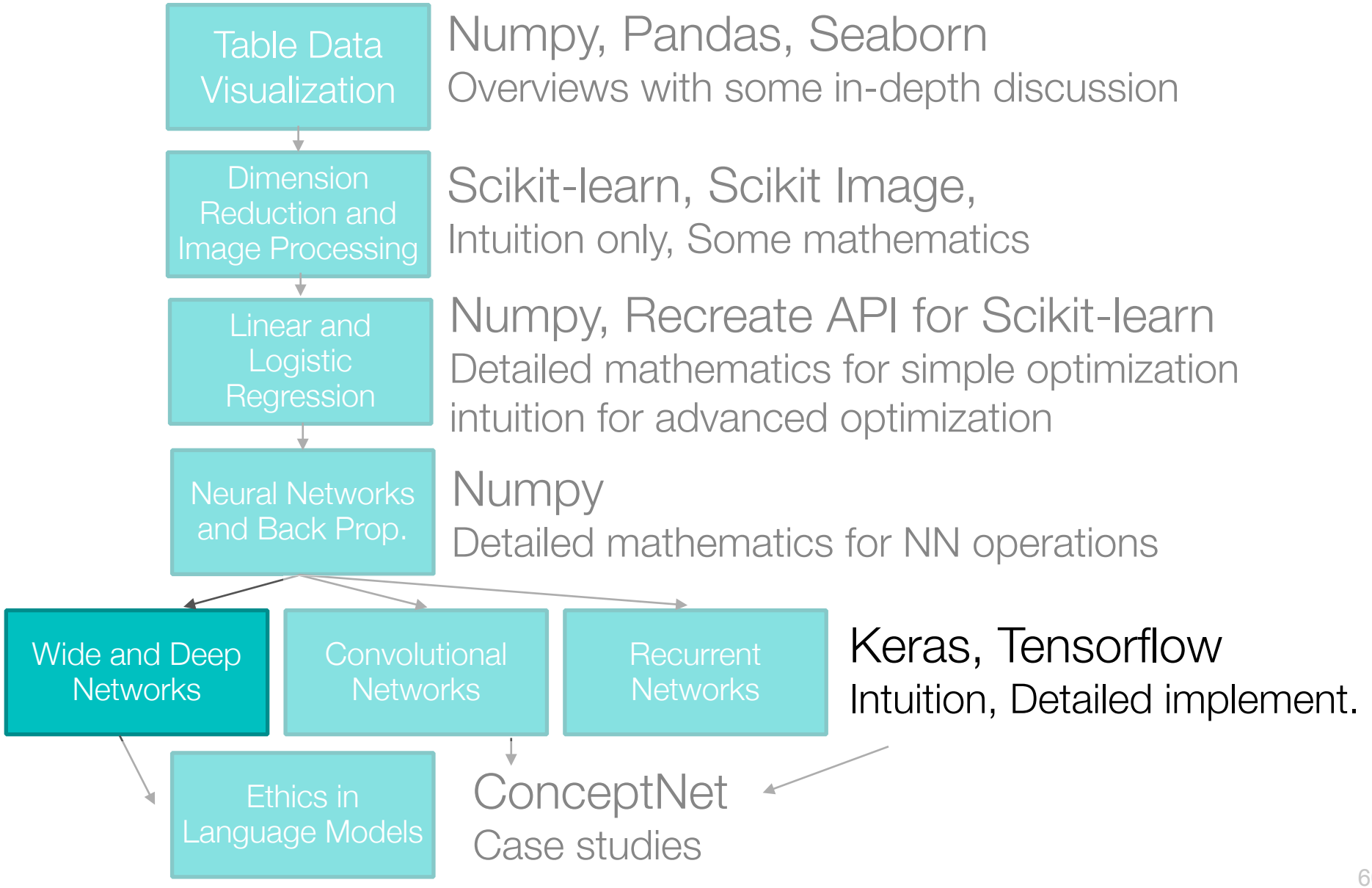
Professor Eric Larson

Wide and Deep Networks

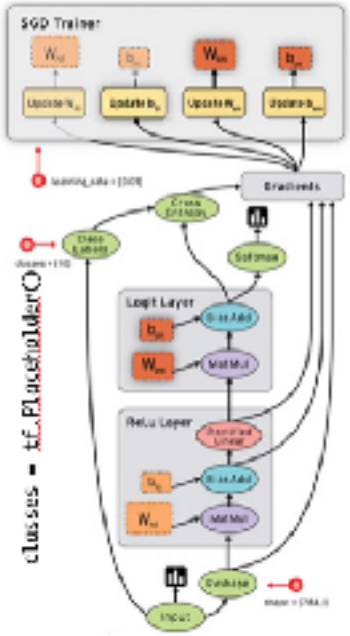
Lecture Agenda

- Logistics:
  - Grading Update
- Agenda:
  - Finish Keras Demo
  - Wide and Deep Networks
  - Wide and Deep Town Hall (if time)

Class Overview, by topic



Last Time: Tensorflow and Keras

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```
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```

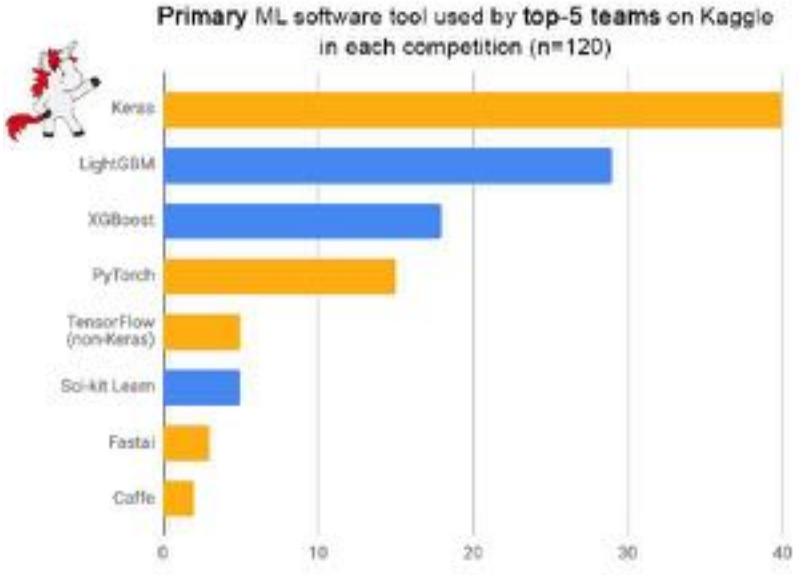

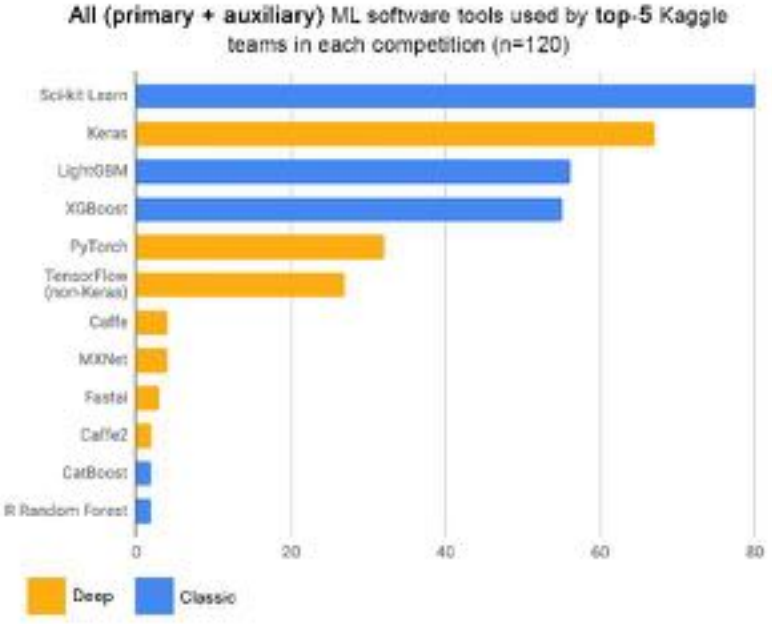

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- **Keras Functional API**
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  - each "function" represents an operation in the NN

Categorical Feature Embeddings Review

- One hot encoded data can be "embedded" through a matrix multiplication (column select)

Trainable Matrix in Network

Reduced Dimensions

0.1	0.3	-0.01	0.15
0.2	1.2	-0.5	0.8

Num Categories

$\cdot$

Eye Color

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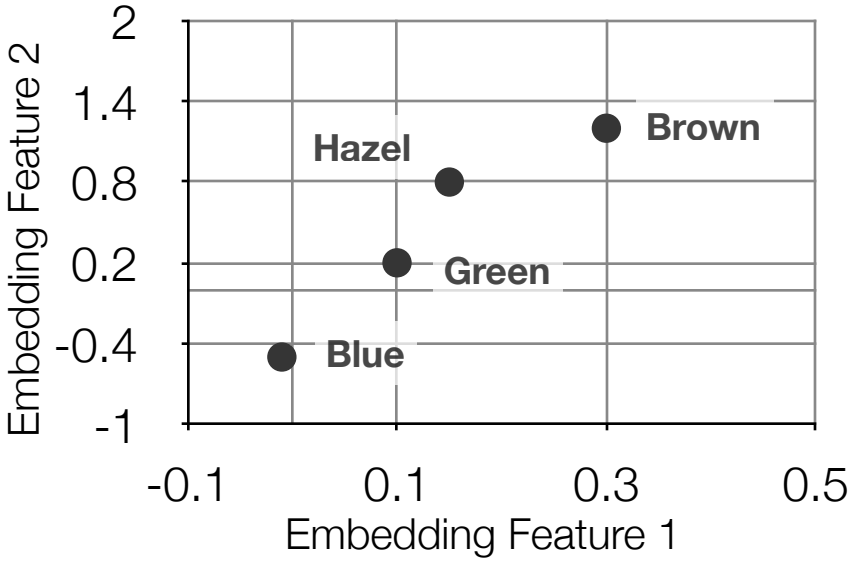
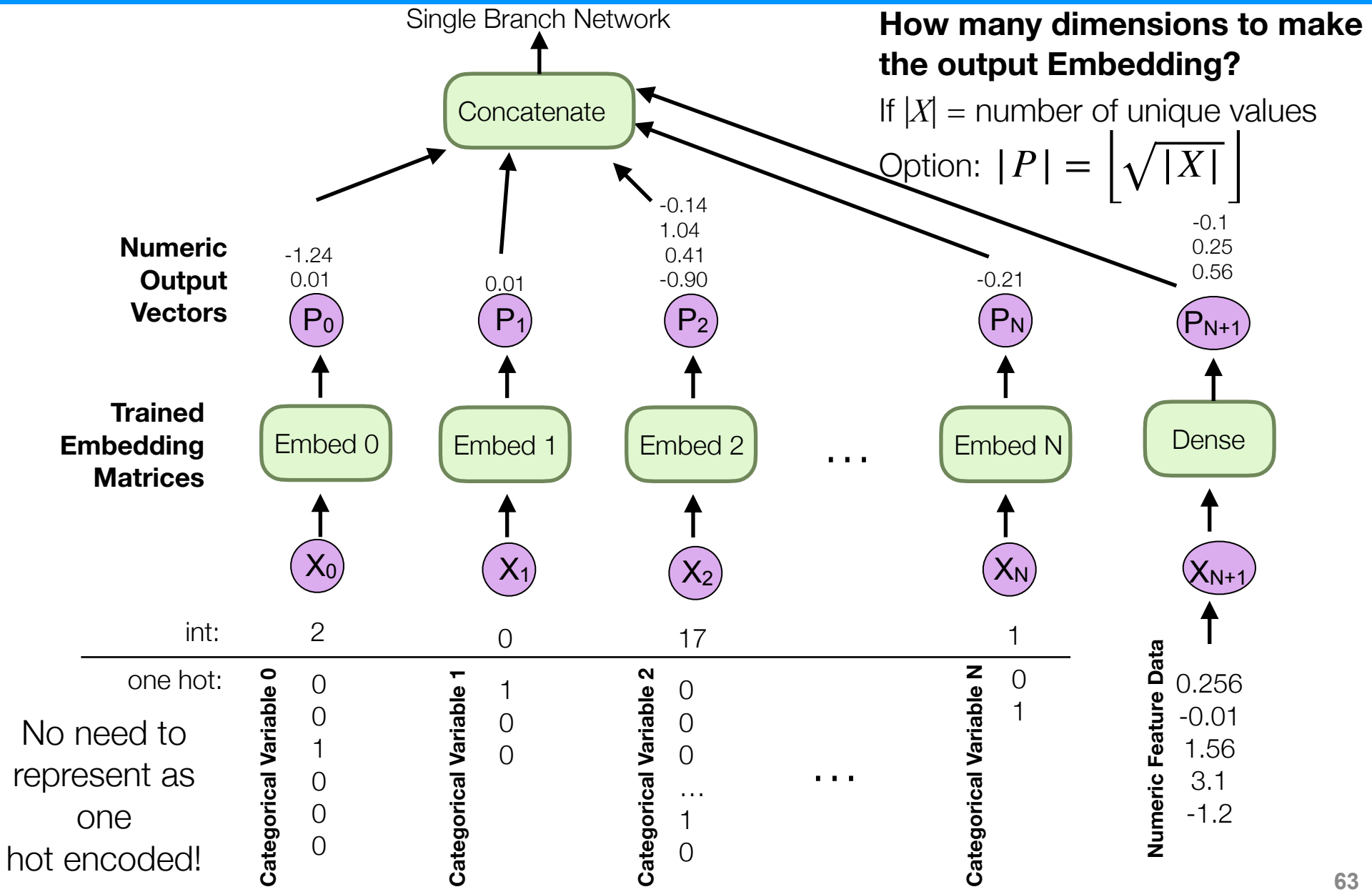


Computationally: there is no need to one hot encode eye color, we can just use the integer to index into column of **embedding matrix**

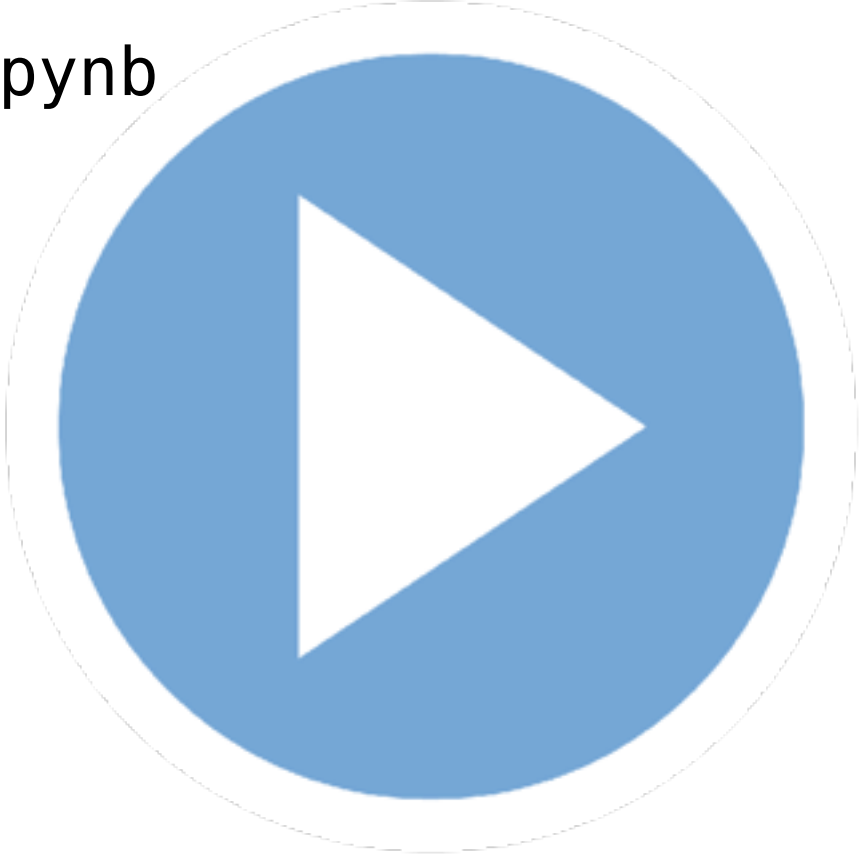
Using Embeddings in Keras Review



Demo

`10. Keras Wide and Deep.ipynb`

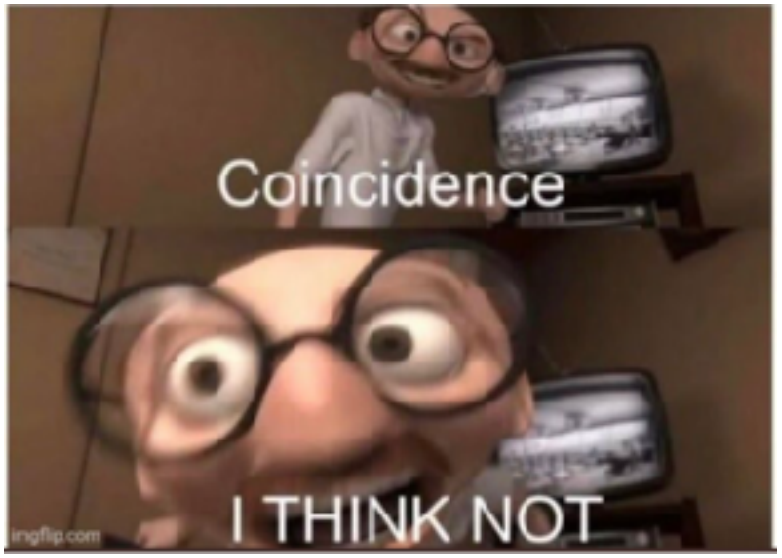
Adding Embedding Branches



Make me slow down if I go too fast!!
By asking questions!

Wide and Deep Networks

When $p < 0.05$



Wide and Deep

Wide & Deep Learning for Recommender Systems

Heng-Tze Cheng, Levent Koc, Jeremiah Harmsen, Tal Shaked, Tushar Chandra, Hrishi Aradhye, Glen Anderson, Greg Corrado, Wei Chai, Mustafa Ispir, Rohan Anil, Zakaria Haque, Lichan Hong, Vihan Jain, Xiaobing Liu, Hemal Shah

Google Inc.*

ABSTRACT

Generalized linear models with nonlinear feature transfor-

have never or rarely occurred in the past. Recommenda-tions based on memorization are usually more topical and

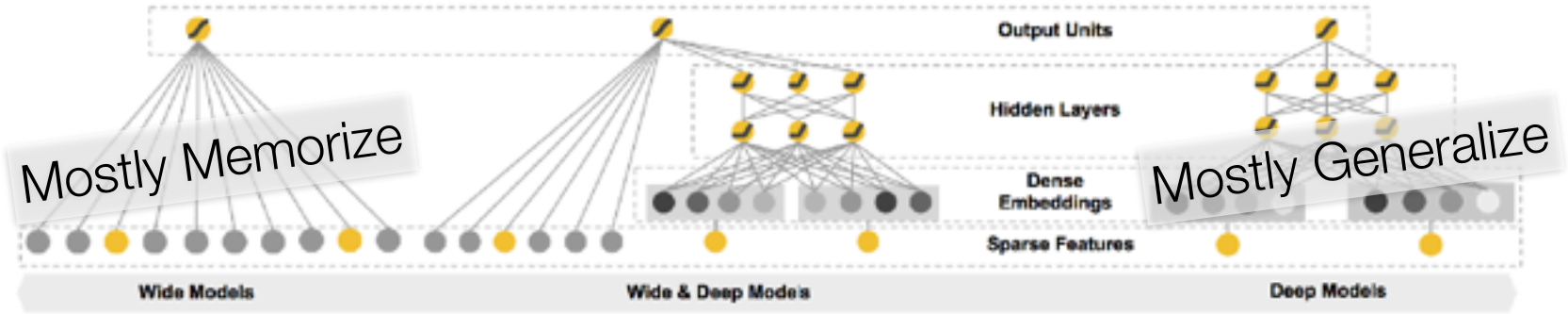
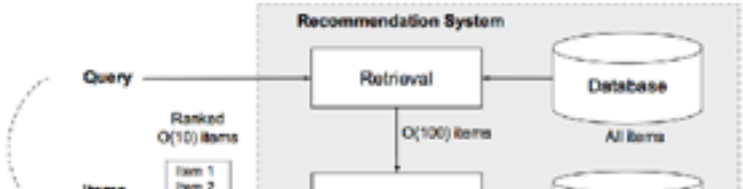


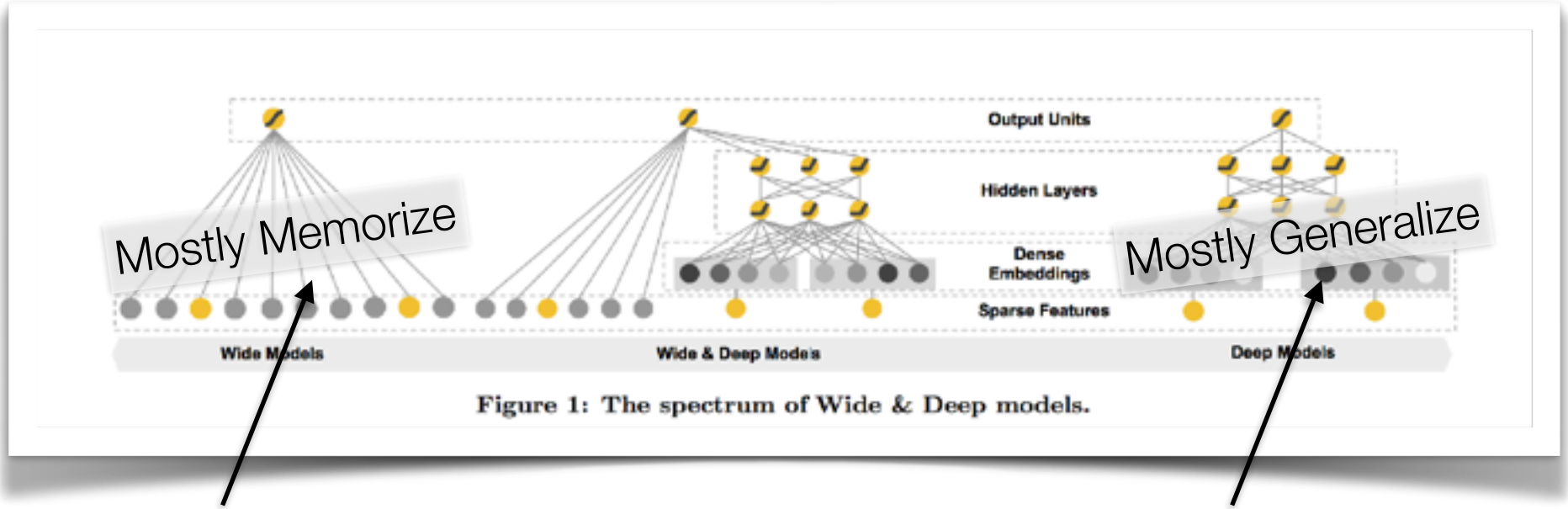
Figure 1: The spectrum of Wide & Deep models.

linear model with feature transformations for generic recommender systems with sparse inputs.

- The implementation and evaluation of the Wide & Deep recommender system productionized on Google



Why wide and deep?



But why memorize?

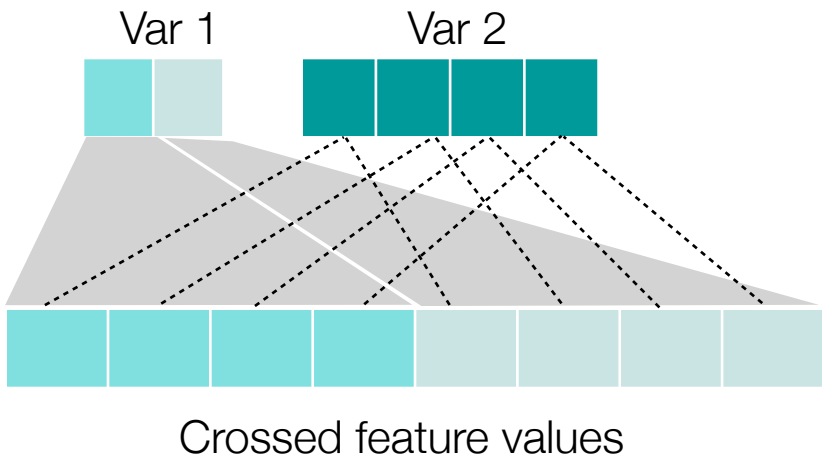
Obvious!

- Categorical values have combinations that repeat!
  - so memorizing these values is not necessarily a bad strategy
  - let's make memorizing easy on one network

Wide networks (Memorize?)

- Wide refers to the expansion of features set
- Crossed feature columns of categorical features

- Movie Rating
  - G
  - PG
  - PG-13
  - R
  - Else
- Movie Genre
  - Action
  - Drama
  - Comedy
  - Horror
  - Else

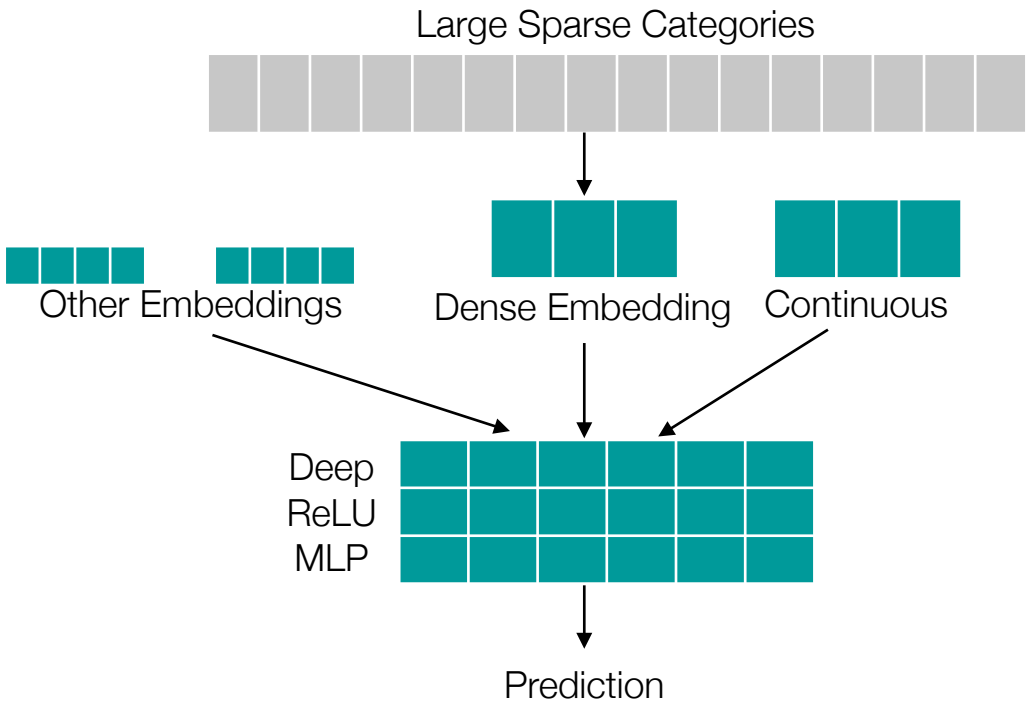


- Crossed feature "Rating-Genre"
  - G-Action, G-Drama, G-Comedy, G-Horror, G-else
  - PG-Action, PG-Drama, PG-Comedy, PG-Horror, G-else
  - and so on … one hot encoded

Sparse Embedding and Deep MLP (Generalize?)

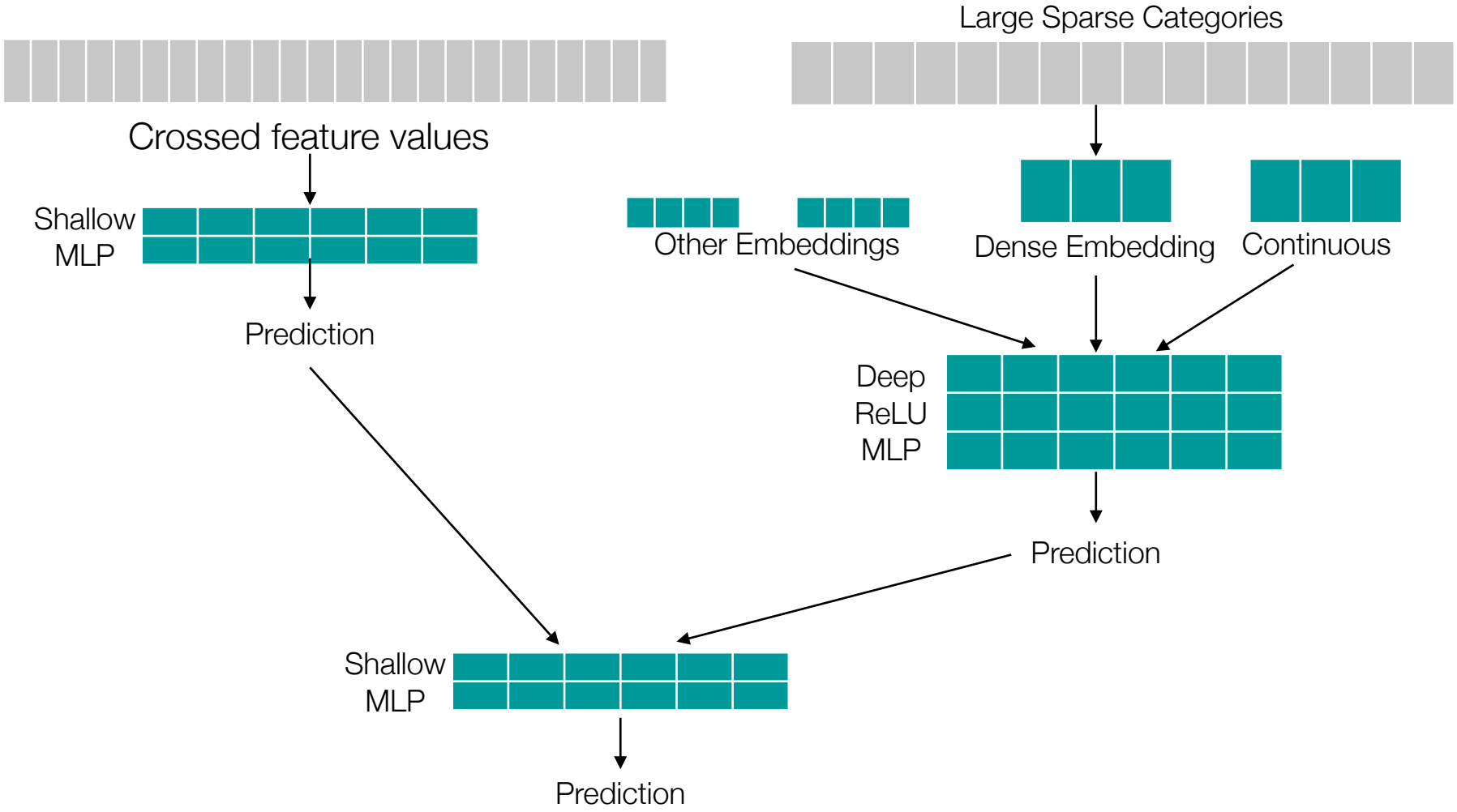
- Deep refers to increasingly narrow hidden layers
- Embed into sparse representations via ReLU

- Movie Actors
  - Armand Assante
  - Meryl Streep
  - Danny Trejo
  - Kevin Bacon
  - Audrey Hepburn
  - …



Combining Memorization and Generalization

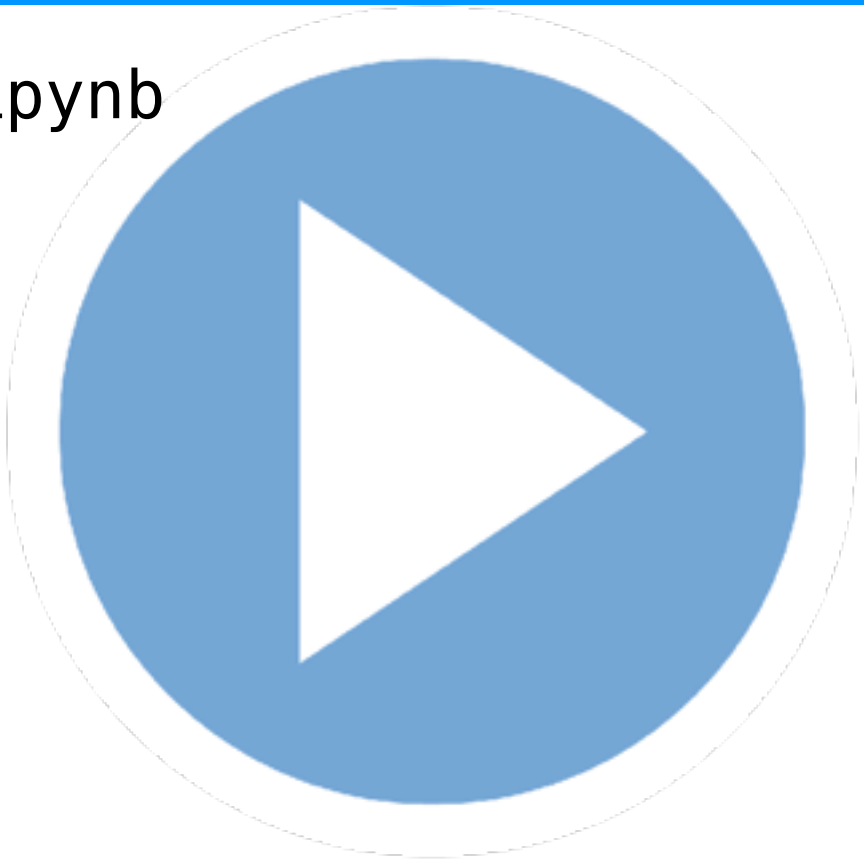
- Deep refers to increasingly narrow hidden layers
- Embed into sparse representations via ReLU



Wide and Deep

Demo

`10. Keras Wide and Deep.ipynb`



The awful dataset:
Toy Census Data Example

Other tutorials:

https://www.tensorflow.org/tutorials/wide_and_deep

Town Hall, Wide and Deep Networks

End of Session

- Next Time:
  - Convolutional Neural Networks