

Lecture Notes for **Machine Learning in Python**



Professor Eric Larson
Feature Spaces + 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

Table Data
Visualization

Numpy, Pandas, Seaborn
Overviews with some in-depth discussion

Dimension
Reduction and
Image Processing

Scikit-learn, Scikit Image,
Intuition only, Some mathematics

Linear and
Logistic
Regression

Numpy, Recreate API for Scikit-learn
Detailed mathematics for simple optimization
intuition for advanced optimization

Neural Networks
and Back Prop.

Numpy
Detailed mathematics for NN operations

Wide and Deep
Networks

Convolutional
Networks

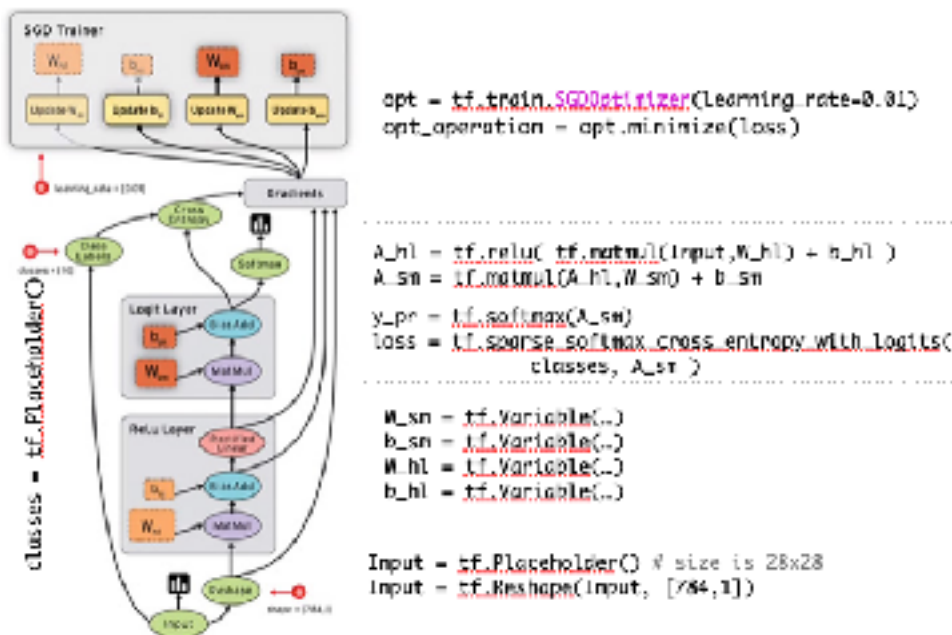
Recurrent
Networks

Keras, Tensorflow
Intuition, Detailed implement.

Ethics in
Language Models

ConceptNet
Case studies

Last Time: Tensorflow and Keras

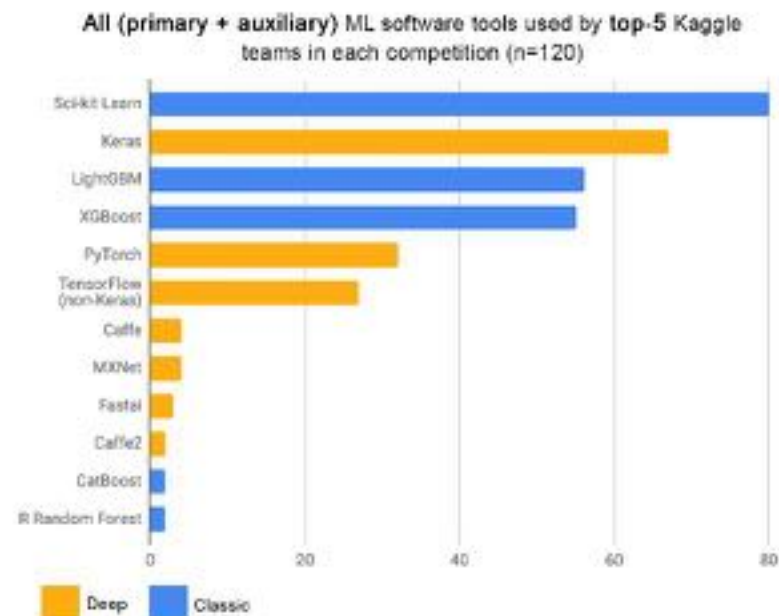
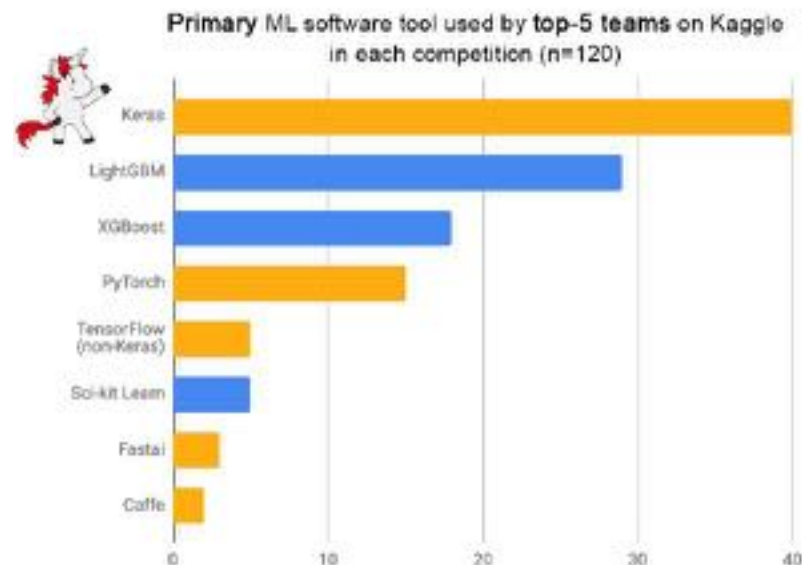


- **Keras Sequential API**

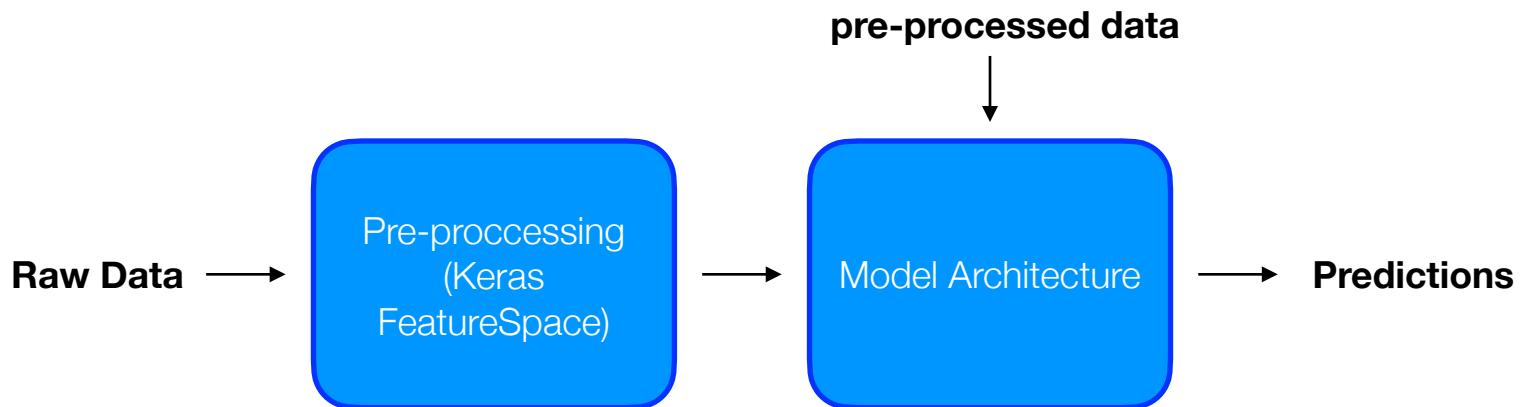
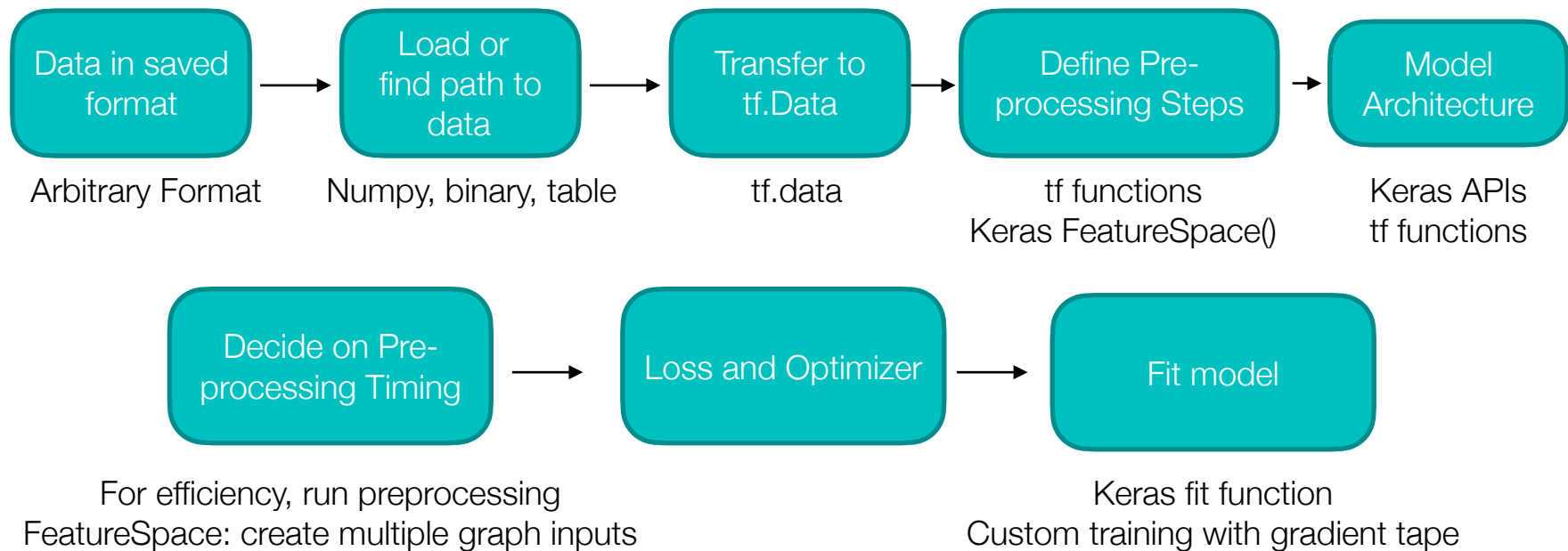
- great for simple, feed forward models

- **Keras Functional API**

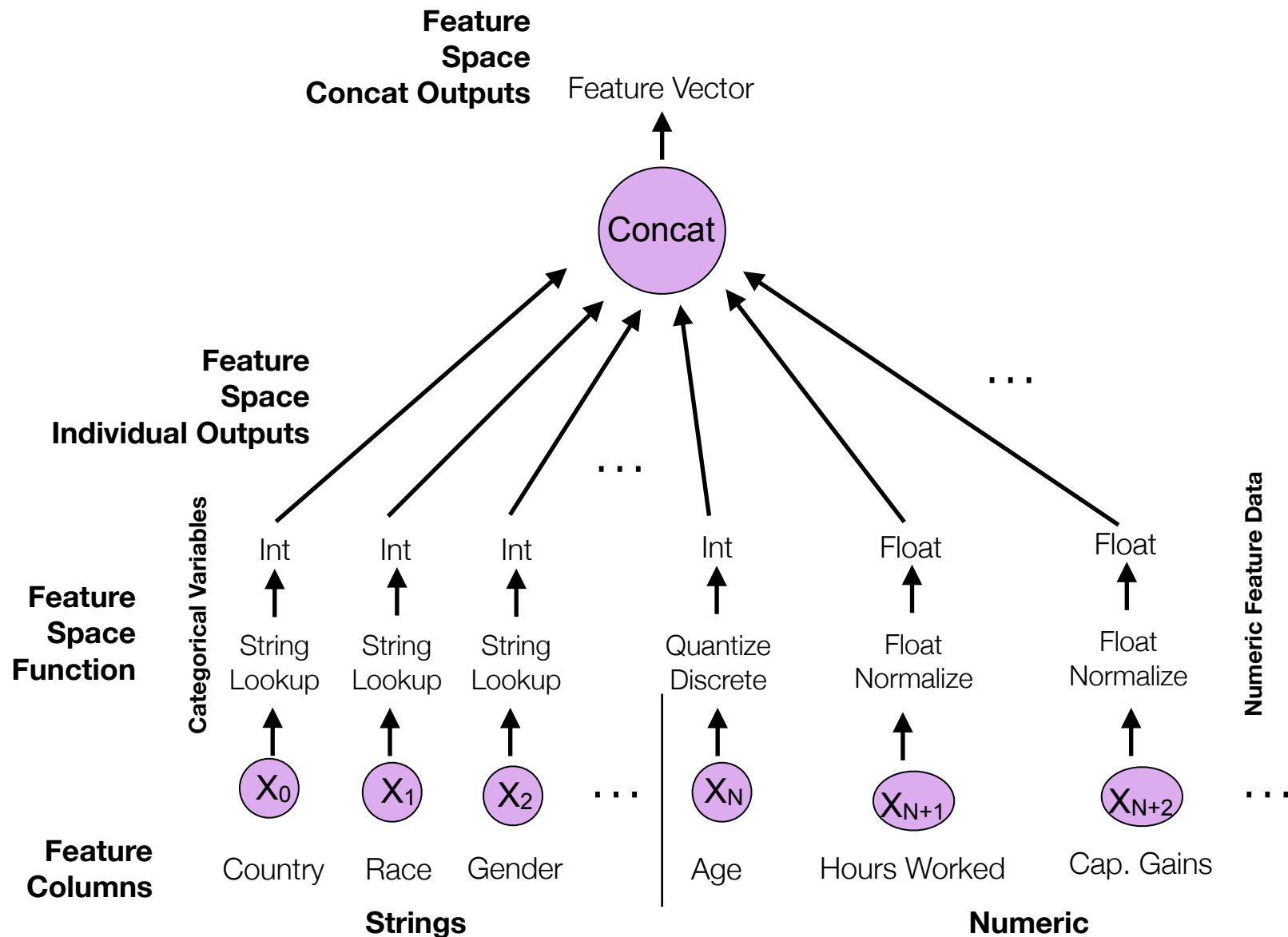
- build models through series of nested functions
- each “function” represents an operation in the NN



Using Keras and Tensorflow



Keras FeatureSpaces



Setting up Feature Spaces



10a. Keras Wide and Deep as TFData.ipynb

Categorical Feature Embeddings Review

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

Trainable Matrix in Network

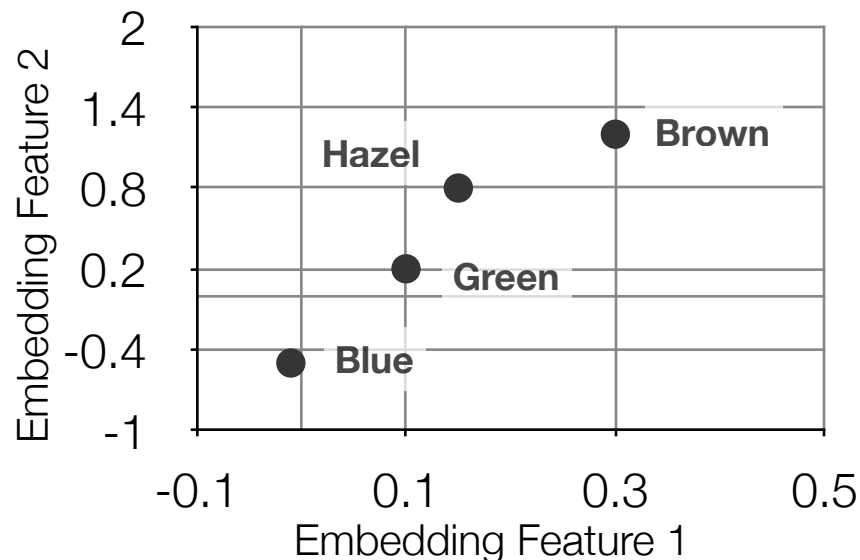
Reduced Dimensions

0.1	0.3	-0.01	0.15
0.2	1.2	-0.5	0.8

Num Categories

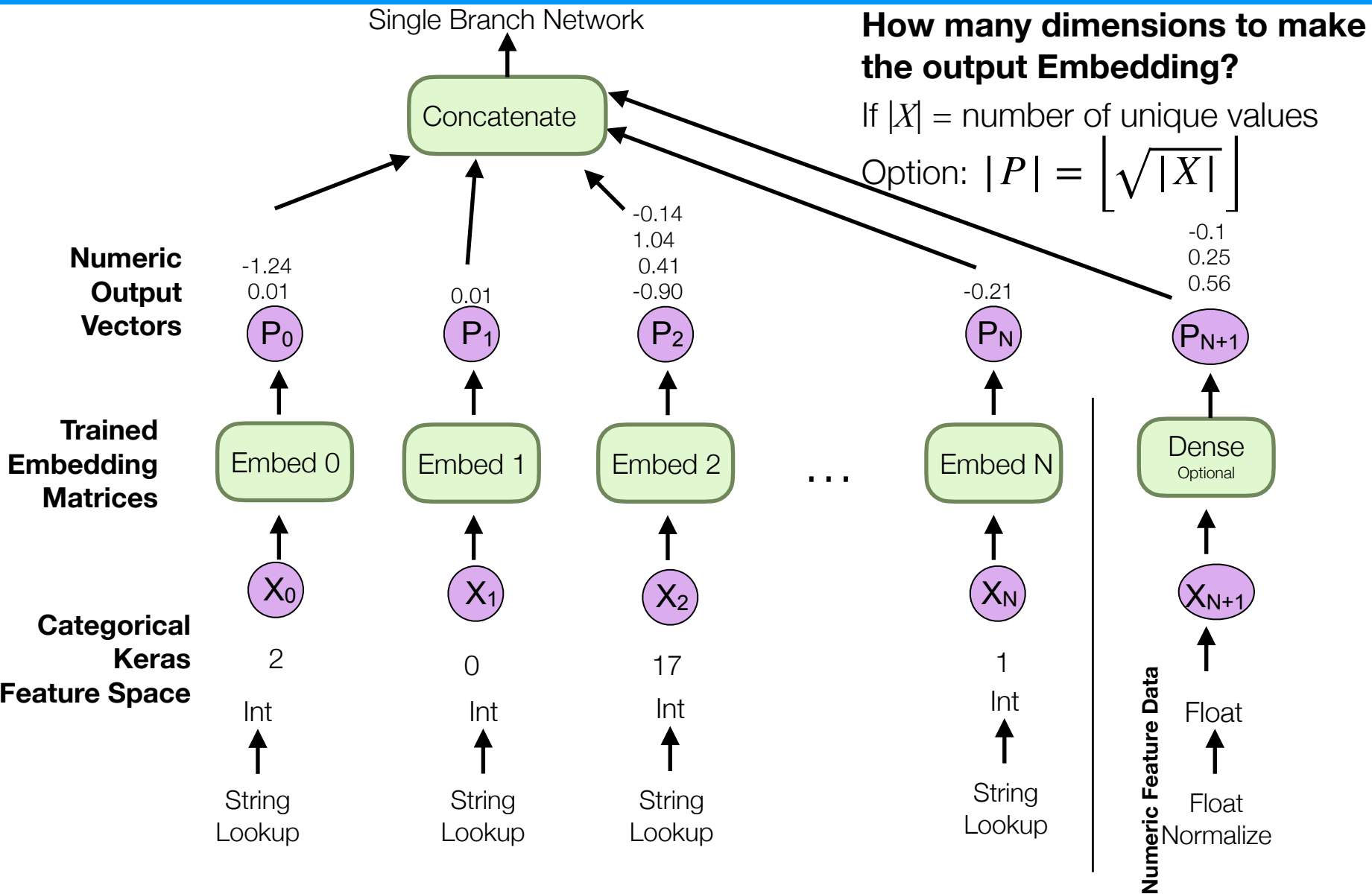
Eye Color

0	Green	→ 0
1	Brown	→ 1
0	Blue	→ 2
0	Hazel	→ 3



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



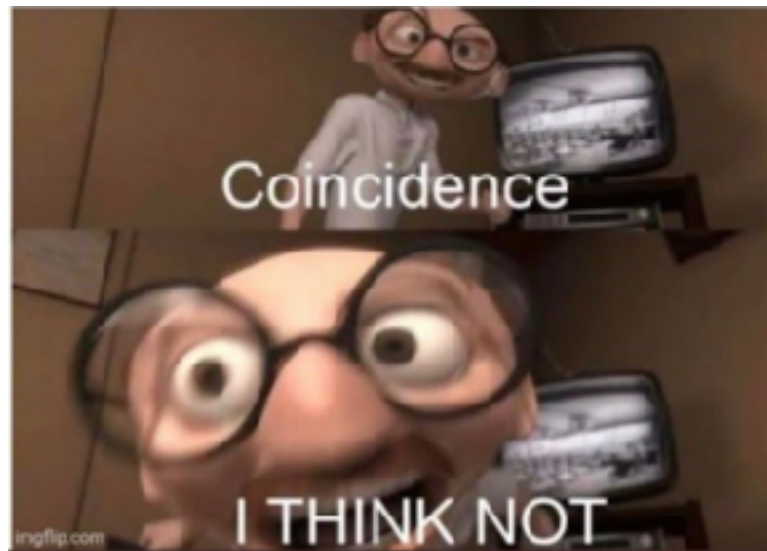
Adding Embedding Branches



10a. Keras Wide and Deep as TFData.ipynb

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. Recommendations based on memorization are usually more topical and

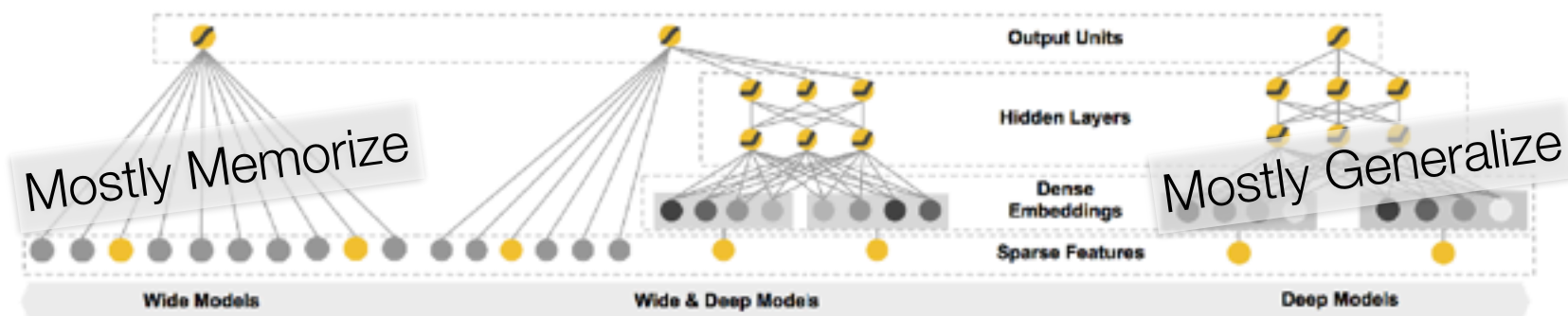
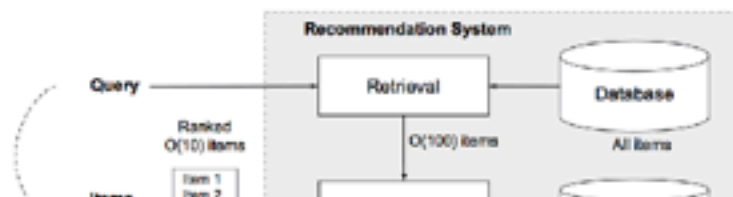


Figure 1: The spectrum of Wide & Deep models.

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?

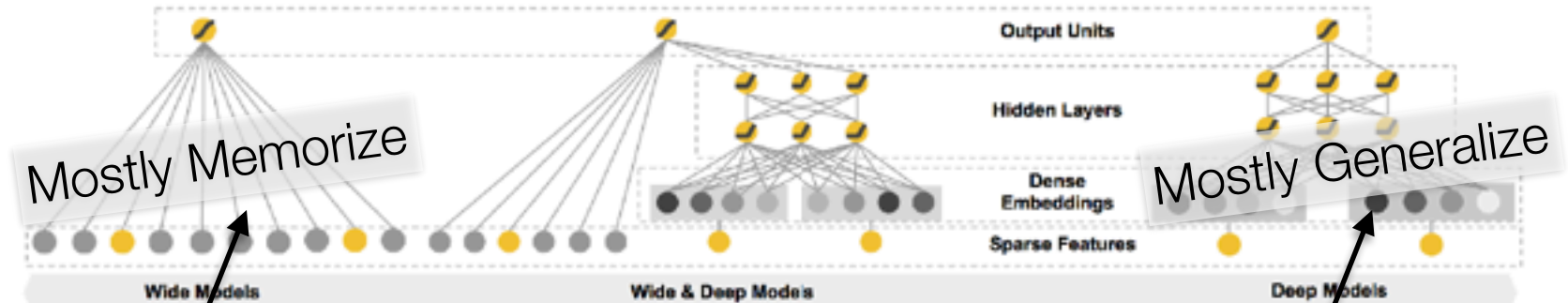


Figure 1: The spectrum of Wide & Deep models.

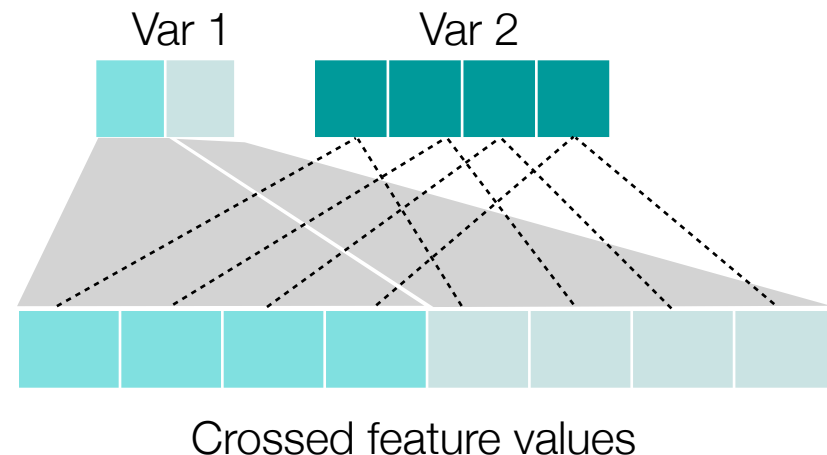
But why memorize?

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?)

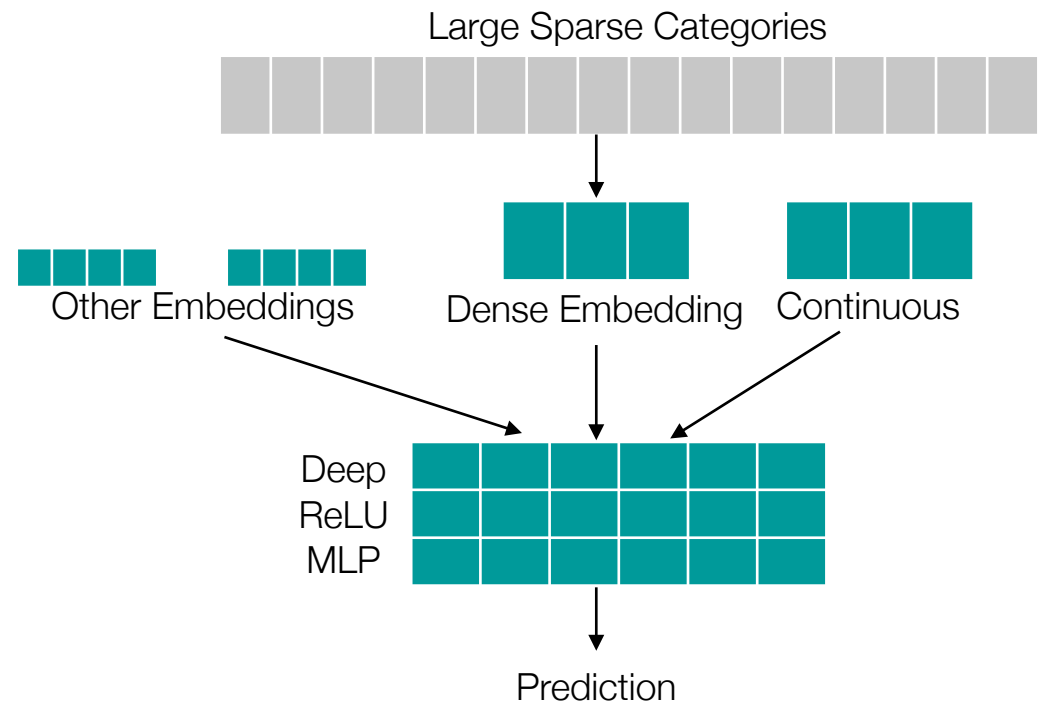
- Wide refers to the expansion of features set
- Crossed feature columns of categorical features
 - Movie Rating
 - G
 - PG
 - PG-13
 - R
 - Else
 - Movie Genre
 - Action
 - Drama
 - Comedy
 - Horror
 - Else
- Crossed feature “Rating-Genre”
 - G-Action, G-Drama, G-Comedy, G-Horror, G-else
 - PG-Action, PG-Drama, PG-Comedy, PG-Horror, G-else
 - and so on ... one hot encoded



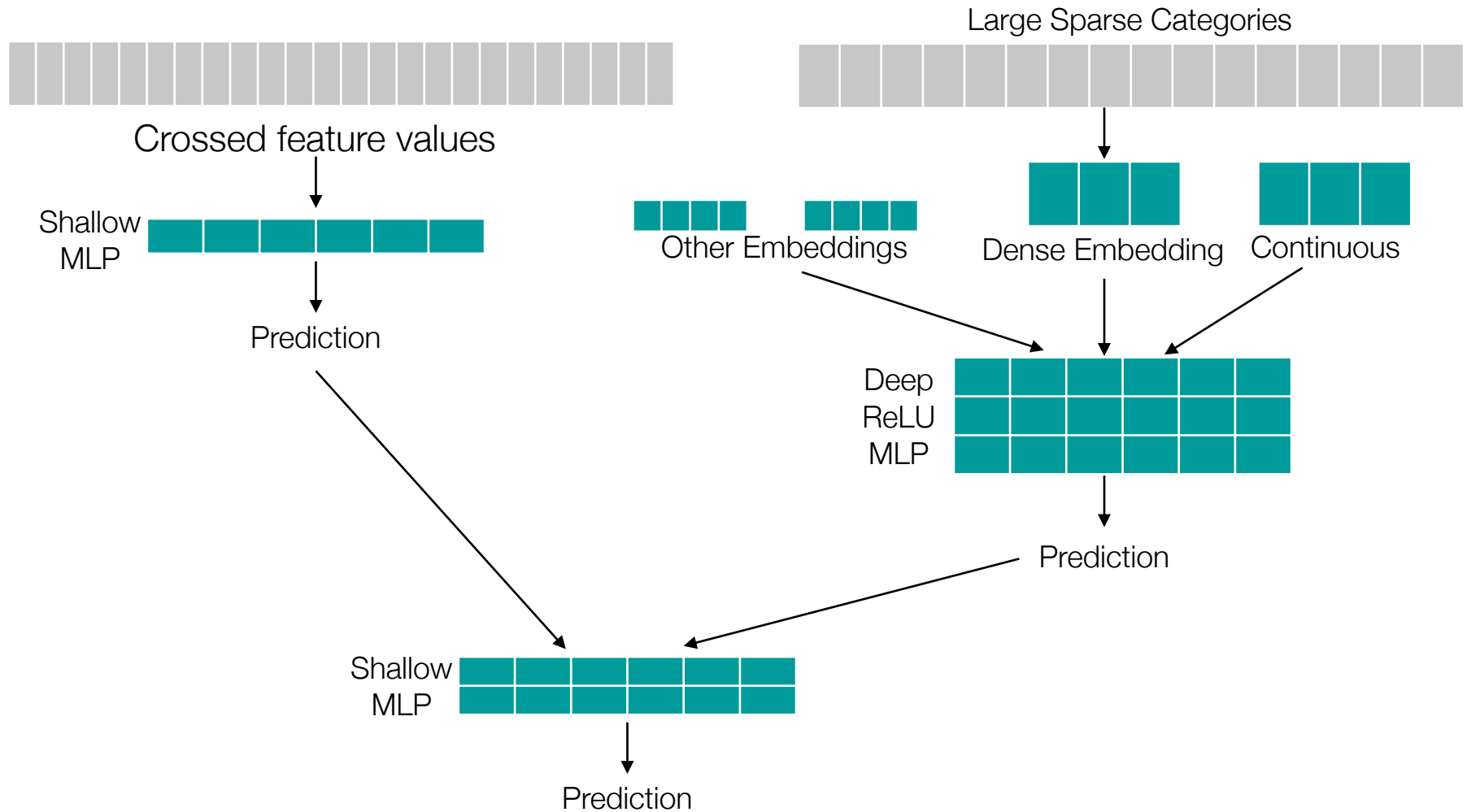
Deep Features: What we have already done!

- Deep refers to increasingly narrow hidden layers
- Essentially the same as what we already did!

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



Combining Memorization and Generalization



Adding Wide Branches



10a. Keras Wide and Deep as TFData.ipynb

Town Hall, Wide and Deep Networks



WHEN VISITING A NEW HOUSE, IT'S
GOOD TO CHECK WHETHER THEY HAVE
AN ALWAYS-ON DEVICE TRANSMITTING
YOUR CONVERSATIONS SOMEWHERE.