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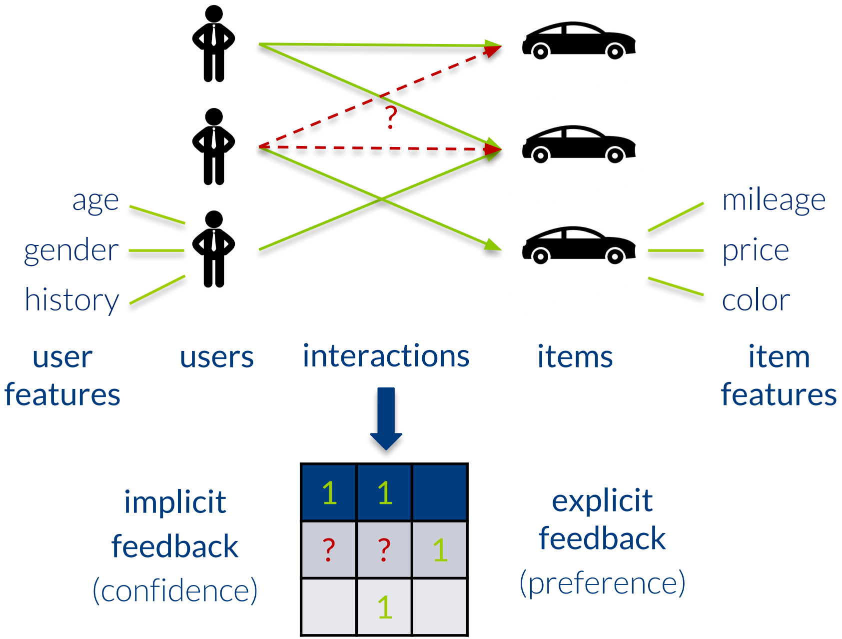
Recommender Systems

Recommender Systems

Introduction



Recommender Systems

Definition

Finds items suited to user’s requirements

Order by relevance

- news
- research papers

⇒ Implicit feedback

Predict ratings

- movies
- music
- apps

⇒ Explicit feedback

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Types

Collaborative Filtering

Content-based Recommender

Cold-start-problem

Sparsity

Obvious recommendations

Demographic Recommender

Context-based Recommender

Recommender Systems

Types

Collaborative Filtering

+

Content-based Recommender

=

Hybrid Recommender

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Factorization Machines - Motivation

- Use information about items to avoid cold start
- Problems
  a. Data contains many features
  b. Data is sparse: many features are zero

How to efficiently compute predictions?

Reduce dimensionality!

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Factorization Machine - Basic Concept

- Implements polynomial regression
  - Extend linear regression by taking interaction between features into account

- Learn high-dimensional representation of input as low-dimensional product of latent factors
  - Model weights as lower-dimensional matrix
  - Can be computed in polynomial time

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Factorization Machine - Training

- Minimize loss function
  - Binary classification: sigmoid function
  - Regression: sum of squared errors

- Add regularization to avoid overfitting

- Many optimization strategies
  - We will use gradient descent

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Factorization Machine - Time To Code

Your turn!

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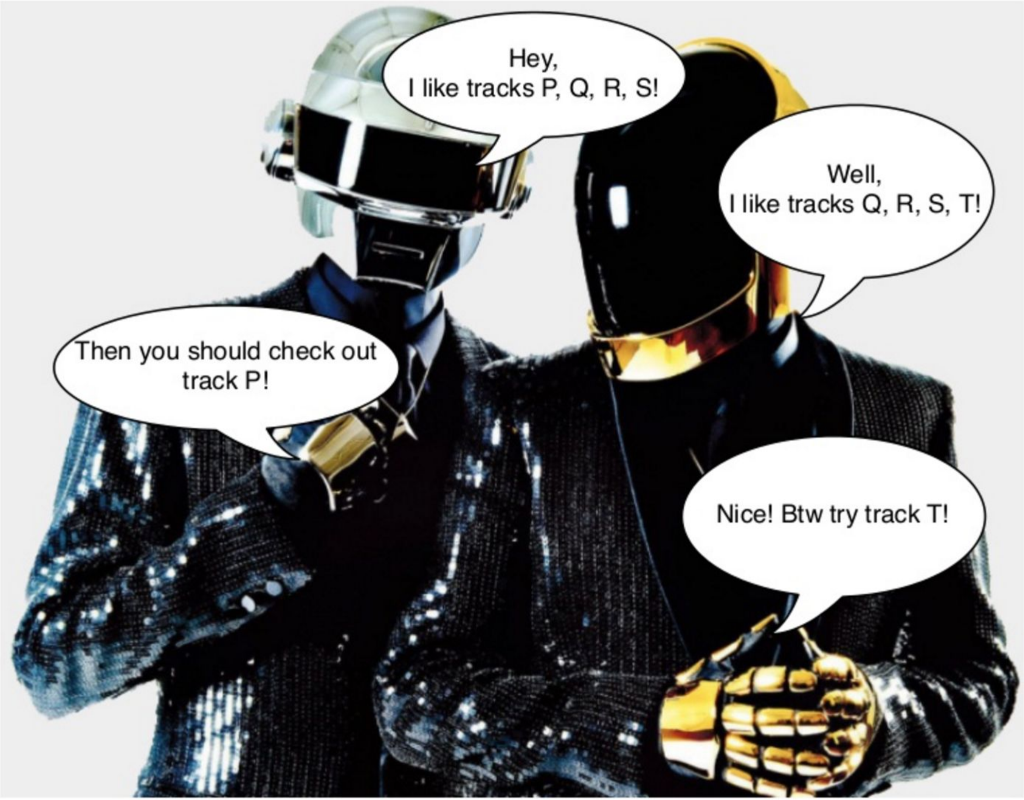
Recommender Systems @ Spotify



Erik Bernhardsson:

http://benanne.github.io/2014/08/05/spotify-cnns.html

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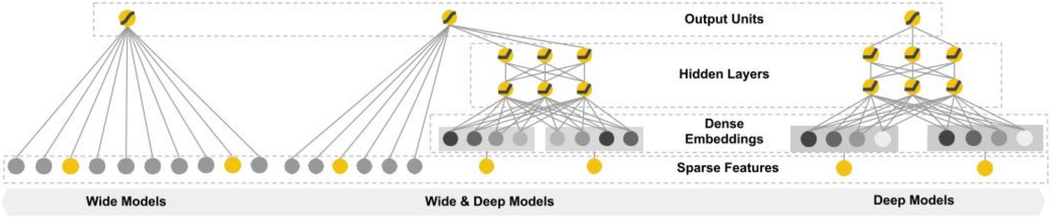
State-of-the-Art: Deep Learning

The ACM Conference Series on Recommender Systems

Wide & Deep Learning for Recommender Systems [Cheng et al., Google; 2016]



- Memorization (wide) + Generalization (deep)
- Joint training of both components
- Google Play

Deep Neural Networks for YouTube Recommendations [Covington et al., Google; 2016]

A Multi-View DL Approach for Cross Domain User Modeling in RS [Elkahky et. al., Microsoft; 2015]

Bayesian Personalized Ranking with Multi-Channel User Feedback [Loni et al.; 2016]

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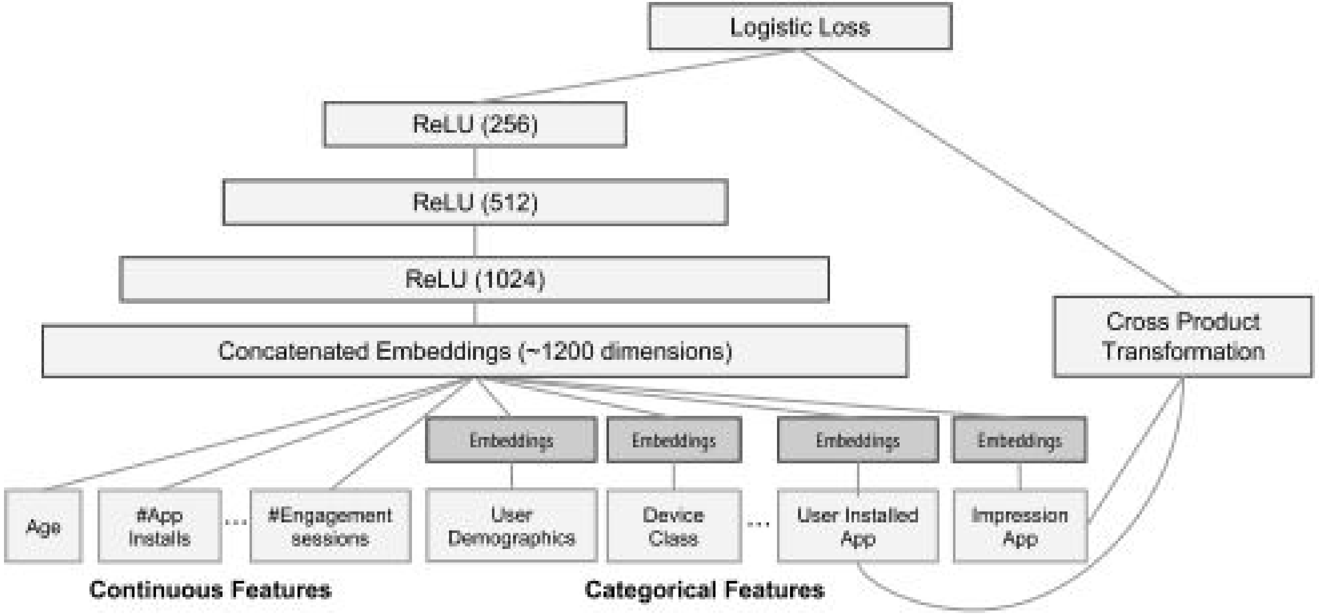
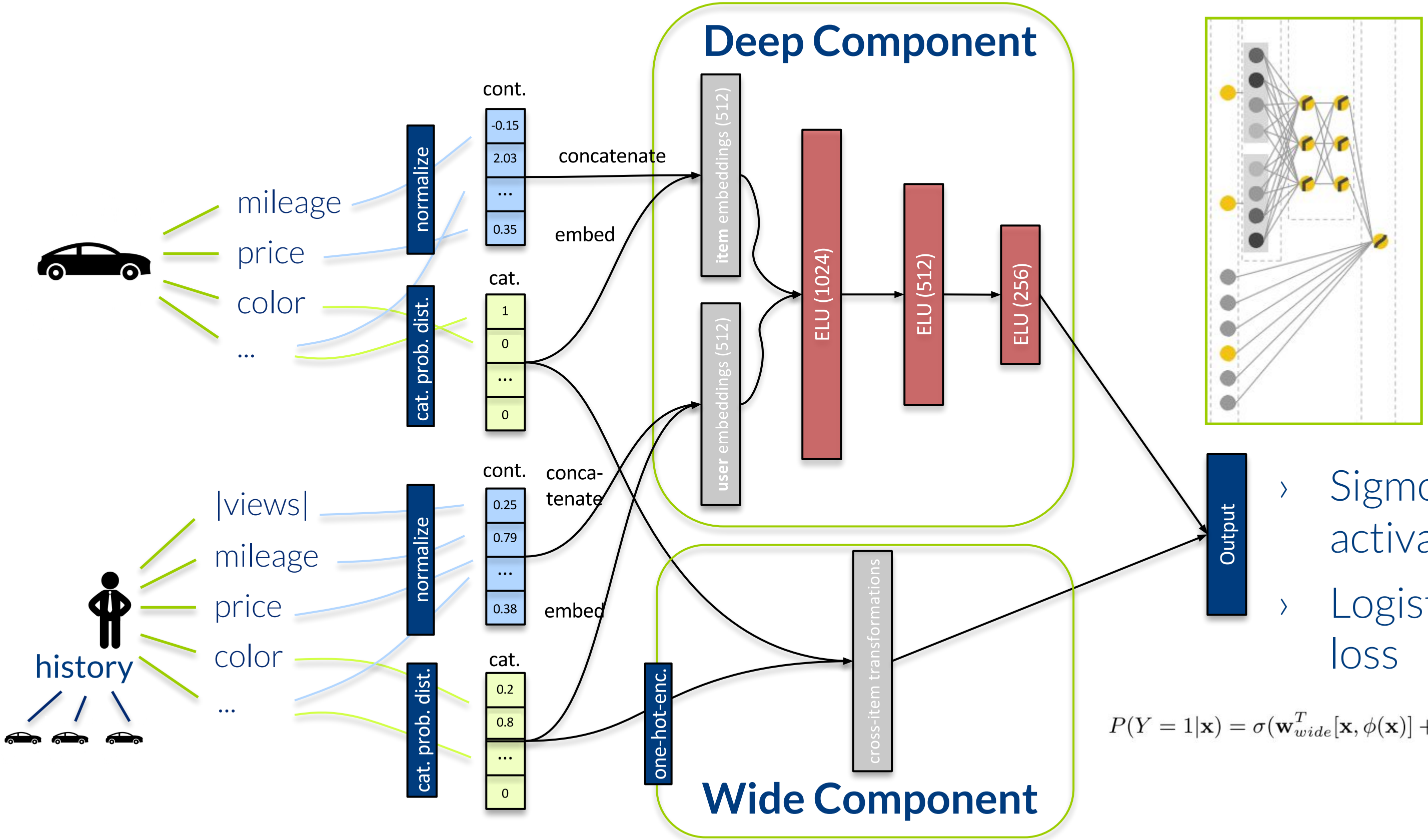
Wide & Deep Learning - Model Architecture



Wide & Deep Learning - Approach



- Sigmoid activation
- Logistic loss

$$P(Y=1|\mathbf{x}) = \sigma(\mathbf{w}_{wide}^T[\mathbf{x}, \phi(\mathbf{x})] + \mathbf{w}_{deep}^T a^{(l_f)} + b)$$

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Wide & Deep Learning - Training

- Minimize loss function
  - Binary classification: logistic loss
  - Regression: sum of squared errors

- Add dropout or weight regularization to avoid overfitting

- Optimize using gradient descent

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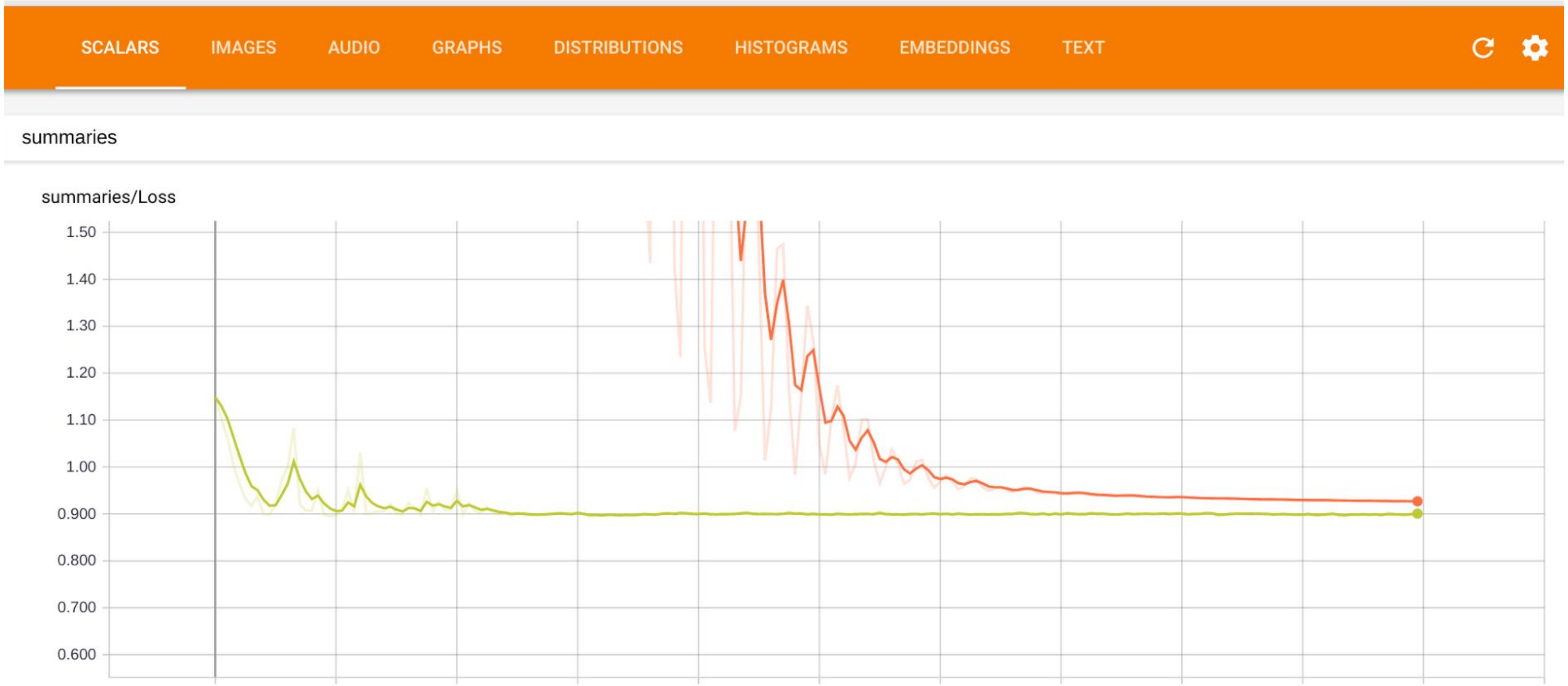
Model Comparison



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Wide & Deep Learning - Time To Code

Your turn!

05_2_wide_n_deep.ipynb

References

[1] Cheng, Heng-Tze, et al. "Wide & deep learning for recommender systems." *Proceedings of the 1st Workshop on Deep Learning for Recommender Systems*. ACM, 2016.

[2] Covington, Paul, Jay Adams, and Emre Sargin. "Deep neural networks for youtube recommendations." *Proceedings of the 10th ACM Conference on Recommender Systems*. ACM, 2016.

[3] Elkahky, Ali Mamdouh, Yang Song, and Xiaodong He. "A multi-view deep learning approach for cross domain user modeling in recommendation systems." *Proceedings of the 24th International Conference on World Wide Web*. ACM, 2015.

[4] Loni, Babak, et al. "Bayesian Personalized Ranking with Multi-Channel User Feedback." *Proceedings of the 10th ACM Conference on Recommender Systems*. ACM, 2016.

Vielen Dank

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