Deep Learning for Recommender Systems

Strata Data Conference New York 2017

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Think Big Analytics
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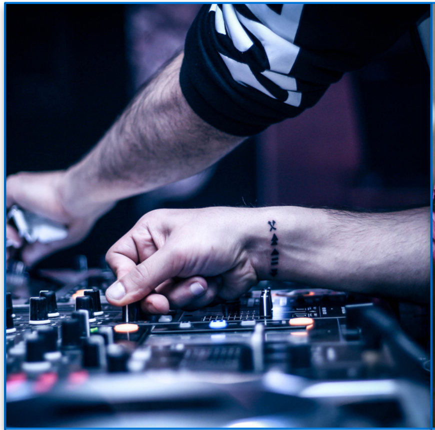
Recommender Systems
Collaborative Filtering
Deep & Wide Learning
Deep Matrix Factorization

Agenda

- Recommender Systems 101
- Collaborative Filtering
- Deep & Wide Learning
- Deep Matrix Factorization

History of Recommendation



Human

- DJ
- Librarian
- Sommelier

Human + Data

- Market Basket
- People you may know
- Job you may be interested in
- Items you may want to consider

Data + Machines

- Deep & Wide Learning
- Deep Matrix Factorization

A family of methods that enable filtering through large observation and information space in order to provide recommendations in the information space [whether] that user does [or does] not have any observation, where the information space is all of the available items that the user could choose or select and observation space is what user experienced or observed so far.

Bugra Akyildiz on Recommender Systems

https://bugra.github.io/work/notes/2014-04-19/alternating-least-squares-method-for-collaborative-filtering/

Recommender Systems Impact

NETFLIX

2/3 of the movies watched are recommended

Google

Recommendations generate 38% more click through on Google News

amazon

70% of Amazon home page is devoted to Recommendations

Spotify

"It's scary how well Spotify Discover Weekly playlists know me."
@Dave_Horwitz

Recommender Systems (Machine Learning Summer School 2014 @ CMU
https://www.slideshare.net/xamat/recommender-systems-machine-learning-summer-school-2014-cmu
Amazon: https://www.monetate.com/infographic/maximize-online-sales-with-product-recommendations

What are recommender systems?

Associations between Things, Concepts, Ideas

Humans learn rules based on experiences and preferences

Human capacity to learn rules from vast amount of data is limited

Variety is increasing on a daily basis as means of production become easier

Recommendation Engines struggle to serve the long tail

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Recommendation System Challenge

Before

- Few Users, Few Items

Users	Item1	Item2	Item3	Item4	Item5
User1	x		x		x
User2	x	x	x		
User3			x	x	X
User4	x	x			x

Today

- Millions & Billions of Users & Items

Users	Item1	Item2	Item3	…	m
User1	x		x		x
User2	x	x	x		
…			x	x	X
n	x	x			x

Sparcity

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Recommendation System Rules

Human Curated Rule

- If User1 like Item1 and Item2, If User2 like Item3 and Item2, then recommend Item3 to User 1
- Does not scale and does not discover latent rules

Rule Mining

- Matrix Factorization
- Predicting Preferences based on past behaviors
- Challenges increase as data sparsity increases

Rule Learning

- Deep Learning based Methods
- Turn sparse features into dense embeddings
- Joint Training Wide & Deep Models
- Deep Matrix Factorization

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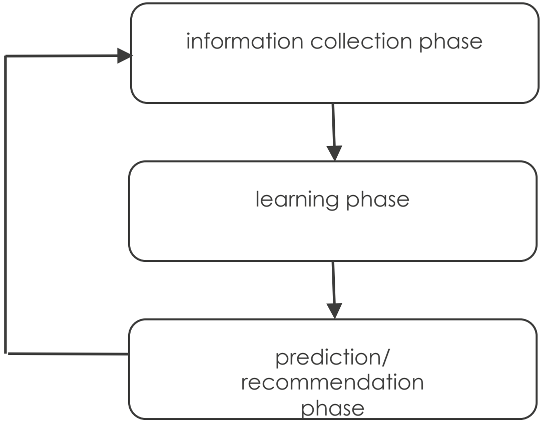
Traditional recommendation approaches

- Collect data -> explicit/implicit/hybrid feedback
- Learn Rules
  - Wine & Cheese
  - Beer & Diapers
- Collaborative Filtering

Traditional recommendation approaches

- Collect data -> explicit/implicit/hybrid feedback

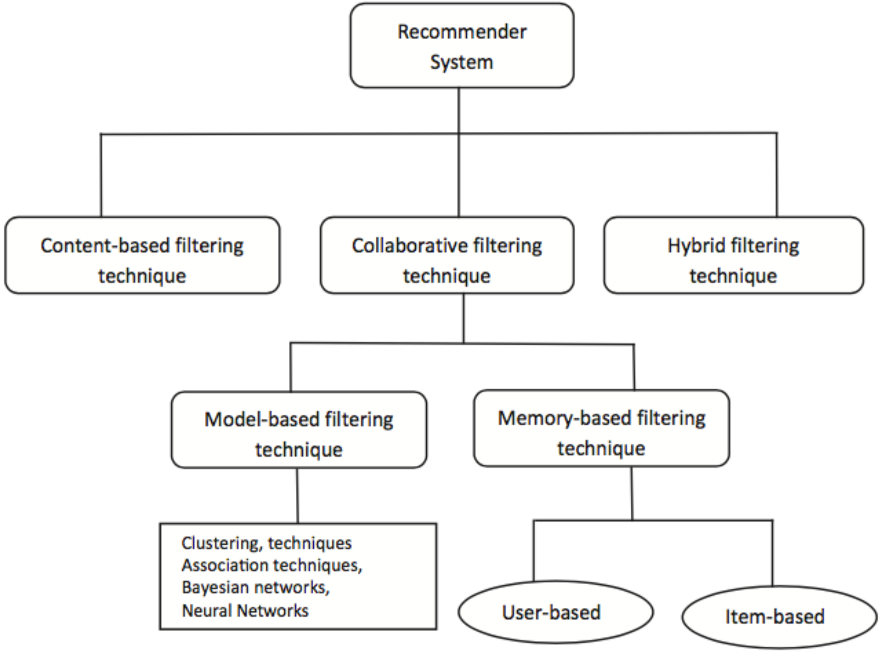


Recommendation phases

source: Recommendation systems: Principles, methods and evaluation

Traditional recommendation approaches

- Learning phase -> prediction recommendation



source: Recommendation systems: Principles, methods and evaluation

Collaborative Filtering

Intuitively:

- Personal tastes correlate for a given domain and information space.
- Users who agreed before are more likely to agree in future on some particular item.
- To approximate the rating of the user, we select users who have somehow similar taste.

  https://bugra.github.io/work/notes/2014-04-19/alternating-least-squares-method-for-collaborative-filtering/

Collaborative Filtering

Advantages over content based methods

- No need to know about item content
  - Content of the item does not necessarily tell the whole story. What features(length, category, actor/actresses) of movie of an item is important for a particular user? No information is necessary for CF.
- "Item cold-start" problem is avoided
  - When the item information is not available, we do not need it as long as some users purchased the item.

  https://bugra.github.io/work/notes/2014-04-19/alternating-least-squares-method-for-collaborative-filtering/

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Collaborative Filtering

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Cold start is a potential problem in computer-based information systems which involve a degree of automated data modelling. Specifically, it concerns the issue that the system cannot draw any inferences for users or items about which it has not yet gathered sufficient information.

  https://bugra.github.io/work/notes/2014-04-19/alternating-least-squares-method-for-collaborative-filtering/

Collaborative Filtering

Advantages over content based methods

- User interest may change over time.
  - Focusing on content solely does not provide any flexibility on the user side. We need to take the user preference change into consideration as well.
- Explainability
  - Rather than rely on content, plausible social rationale for the user can result (eg: "You will like this product because other users like you like the product").
- Capture subtlety
  - This is generally true for latent factor models. If most of the users are buying two unrelated items, then it is likely another user who shares the same taste of the larger set of users is likely to buy that unrelated thing, which brings serendipity to the table.

  https://bugra.github.io/work/notes/2014-04-19/alternating-least-squares-method-for-collaborative-filtering/

Collaborative Filtering

Disadvantages vs content based methods

- Sparsity of user preference and Scalability in computation
  - User preference sparsity makes it hard to find users who share similar taste
  - Large sparse matrices make hard to do computation in general.
- Privacy Concerns
  - Some users may not want their preference and taste available on the website even in an implicit form.
- Synonym issue needs to be handled properly and normalized
  - Film-movie corresponds to the same thing, if one user buys comedy and the other buys "funny movies", they should be treated as same in order to improve both recommendations and not separate the things that are inherently alike.

  https://bugra.github.io/work/notes/2014-04-19/alternating-least-squares-method-for-collaborative-filtering/

Collaborative Filtering

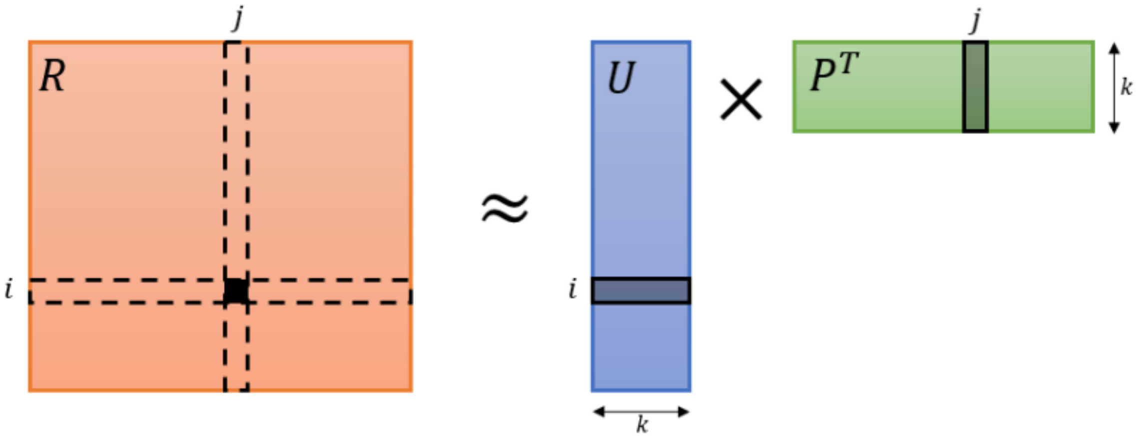
Disadvantages vs content based methods

- Gray Sheep
  - There may be people whose taste and preference do not *consistently* agree with other users' preference. Recommendations for these users may not make sense as their taste is quite distinct from others.
- Shilling Attack
  - People who like one brand may give consistently high scores to that brand and give poor scores to the competitors no matter what their real experience are.

  https://bugra.github.io/work/notes/2014-04-19/alternating-least-squares-method-for-collaborative-filtering/

ALS Method for Collaborative Filtering

- **Matrix Factorization**



https://datasciencemadesimpler.wordpress.com/tag/alternating-least-squares/

ALS Method for Collaborative Filtering

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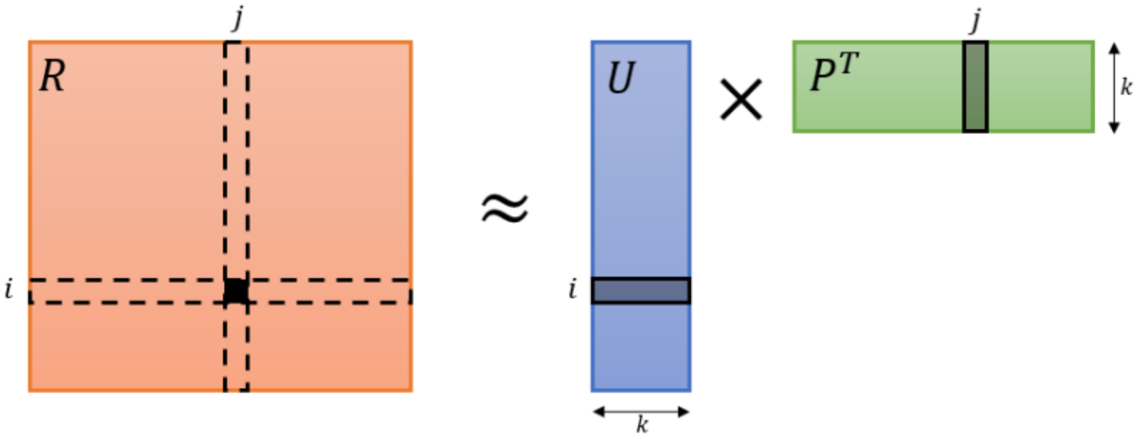


$$J = \left\| R - U \times P^T \right\|_2 + \lambda \left(\|U\|_2 + \|P_2\| \right)$$

https://datasciencemadesimpler.wordpress.com/tag/alternating-least-squares/

ALS Method for Collaborative Filtering

- **Alternating Least Squares**

$$||R - U \times P^T||_2 = \sum_{i,j} (R_{i,j} - u_i \times p_j)$$

Solve for β by minimizing square errors: $||y - X\beta||_2$

https://datasciencemadesimpler.wordpress.com/tag/alternating-least-squares/

Matrix Factorization Notebook

- Demonstrate how to use the TensorFlow API to implement a matrix factorization model (ALS)

Our Dataset

- Our dataset: Movielens 1m dataset
    - http://files.grouplens.org/datasets/movielens/ml-1m.zip

Our Dataset

- movies.dat

```
1::Toy Story (1995)::Animation|Children's|Comedy
2::Jumanji (1995)::Adventure|Children's|Fantasy
3::Grumpier Old Men (1995)::Comedy|Romance
4::Waiting to Exhale (1995)::Comedy|Drama
5::Father of the Bride Part II (1995)::Comedy
```

- users.dat

```
1::F::1::10::48067
2::M::56::16::70072
3::M::25::15::55117
4::M::45::7::02460
```

- ratings.dat

Columns are separated by ::

```
1::1193::5::978300760
1::661::3::978302109
1::914::3::978301968
1::3408::4::978300275
```

```
- Gender is denoted by a "M" for male and "F" for female
- Age is chosen from the following ranges:

    *  1:  "Under 18"
    * 18:  "18-24"
    * 25:  "25-34"
    * 35:  "35-44"
    * 45:  "45-49"
    * 50:  "50-55"
    * 56:  "56+"

- Occupation is chosen from the following choices:

    *  0:  "other" or not specified
    *  1:  "academic/educator"
    *  2:  "artist"
    *  3:  "clerical/admin"
    *  4:  "college/grad student"
    *  5:  "customer service"
    *  6:  "doctor/health care"
    *  7:  "executive/managerial"
    *  8:  "farmer"
    *  9:  "homemaker"
    * 10:  "K-12 student"
    * 11:  "lawyer"
    * 12:  "programmer"
    * 13:  "retired"
    * 14:  "sales/marketing"
    * 15:  "scientist"
    * 16:  "self-employed"
    * 17:  "technician/engineer"
    * 18:  "tradesman/craftsman"
    * 19:  "unemployed"
    * 20:  "writer"
```

The Goal

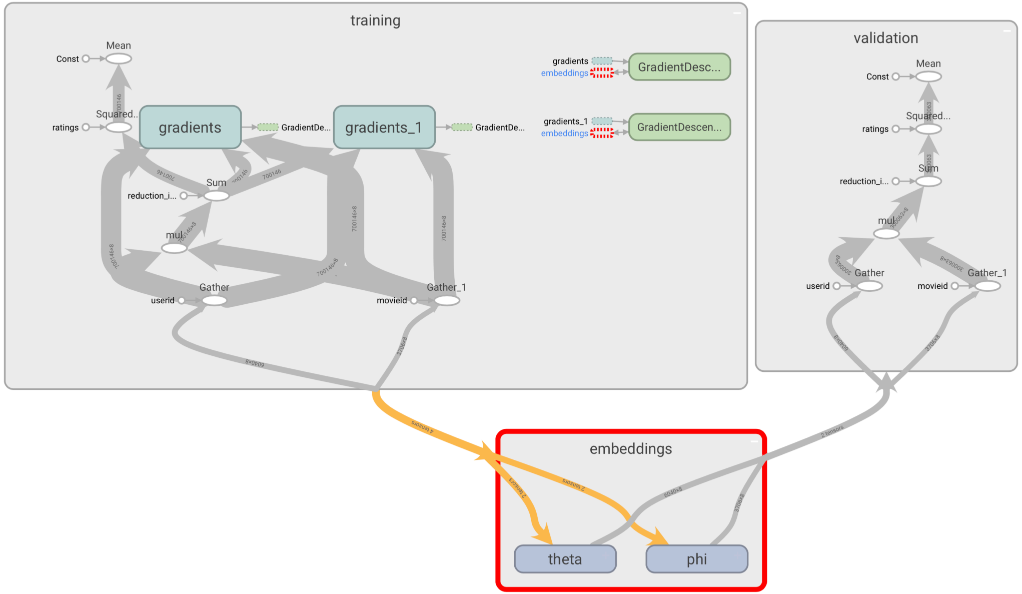
- Our Goal is to predict the rating for a given pair of user id and movie id

	gender	userid	movieid	age_desc	occ_desc	title	genre	rating	prediction (rnd.)	prediction (prc.)
49536	M	2507	171	25-34	college/grad student	Jeffrey (1995)	Comedy	4	4	3.923754
299582	M	984	1197	50-55	self-employed	Princess Bride, The (1987)	Action|Adventure|Comedy|Romance	4	4	3.519701
738324	F	3308	2724	18-24	writer	Runaway Bride (1999)	Comedy|Romance	4	3	2.556867
900461	M	5795	3432	25-34	academic/educator	Death Wish 3 (1985)	Action|Drama	1	1	1.461695
531555	M	5627	1967	25-34	other or not specified	Labyrinth (1986)	Adventure|Children's|Fantasy	2	3	2.547536

MF Accuracy: 45.008881%

Implementation Steps

- Load data
- Set up our parameters: θ and φ
- Define non-trainable variables: user ids, movie ids and ratings
- Calculate the prediction and cost
- Train and evaluate the model



tensorboard --logdir=path/to/log-directory

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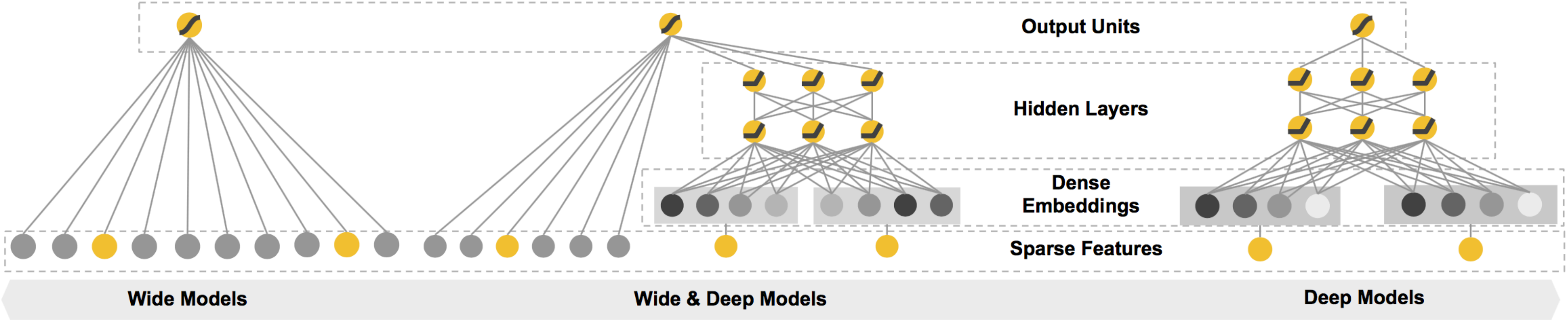
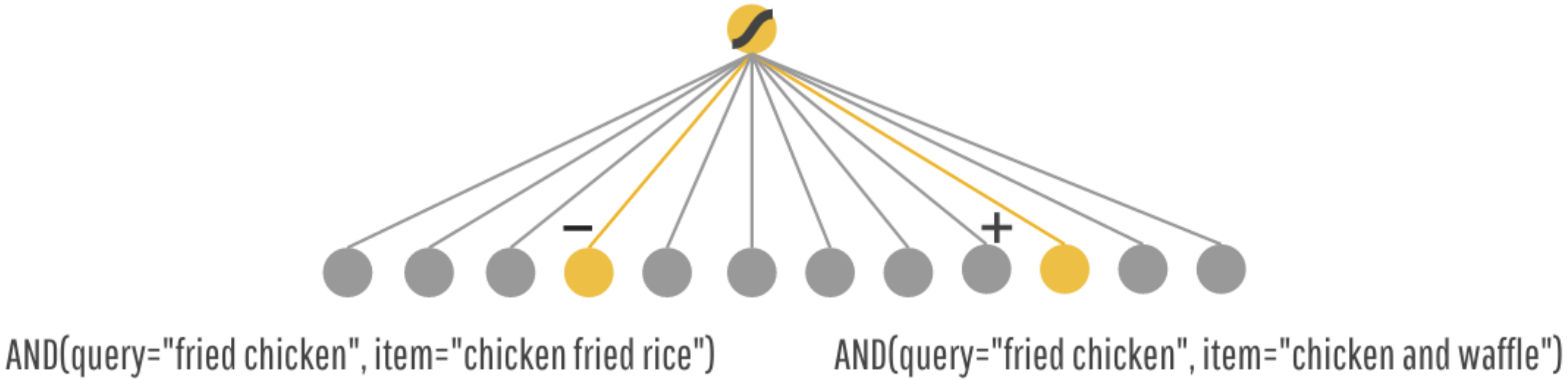
Wide & Deep Learning for Recommender Systems



https://research.googleblog.com/2016/06/wide-deep-learning-better-together-with.html

Wide Model



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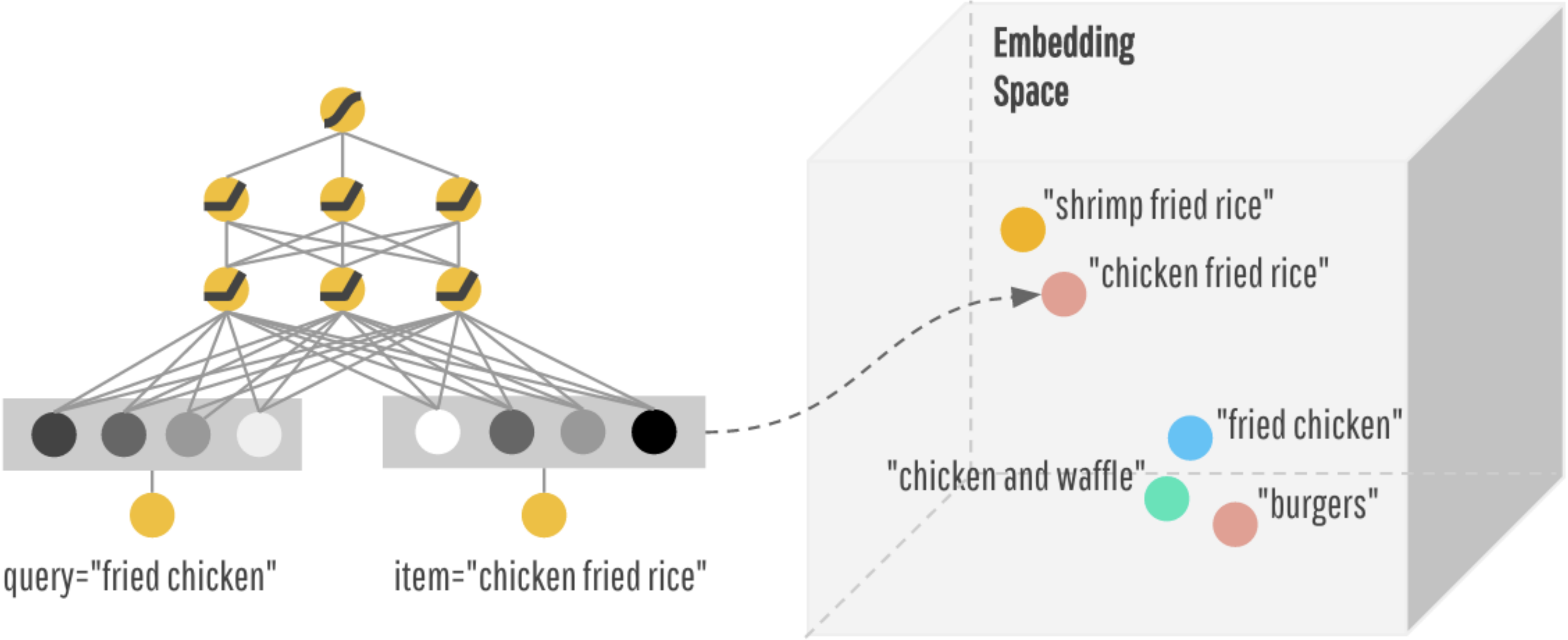
Deep Model



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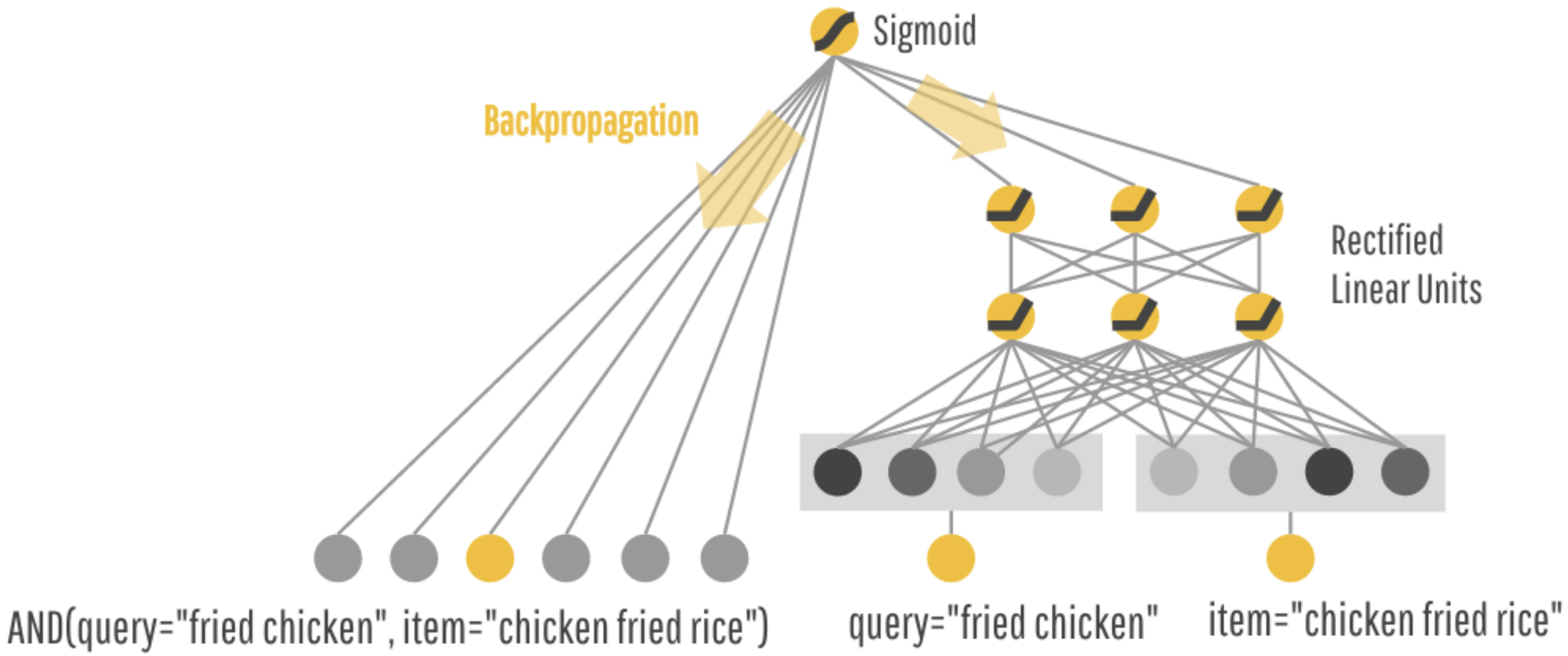
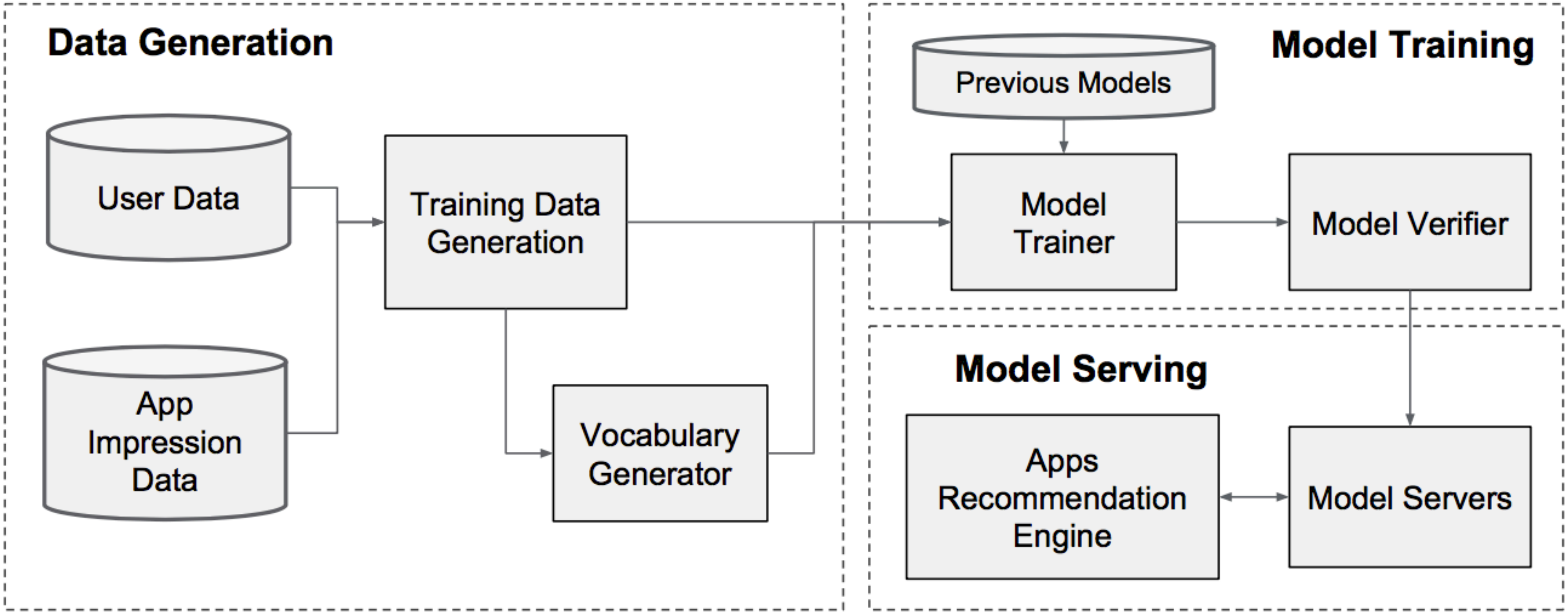
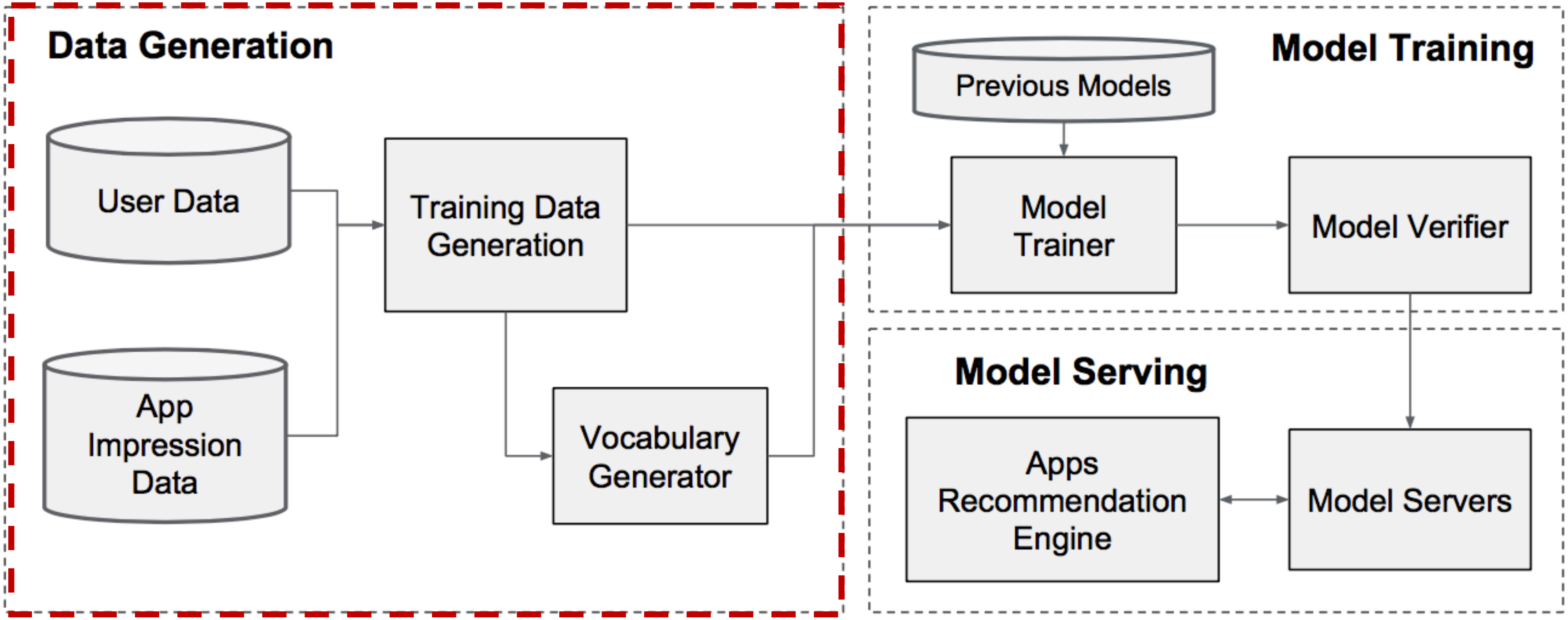
Wide & Deep Model



Wide & Deep


Data Generation
User Data
App Impression Data
Training Data Generation
Vocabulary Generator
Model Training
Previous Models
Model Trainer
Model Verifier
Model Serving
Apps Recommendation Engine
Model Servers

Wide & Deep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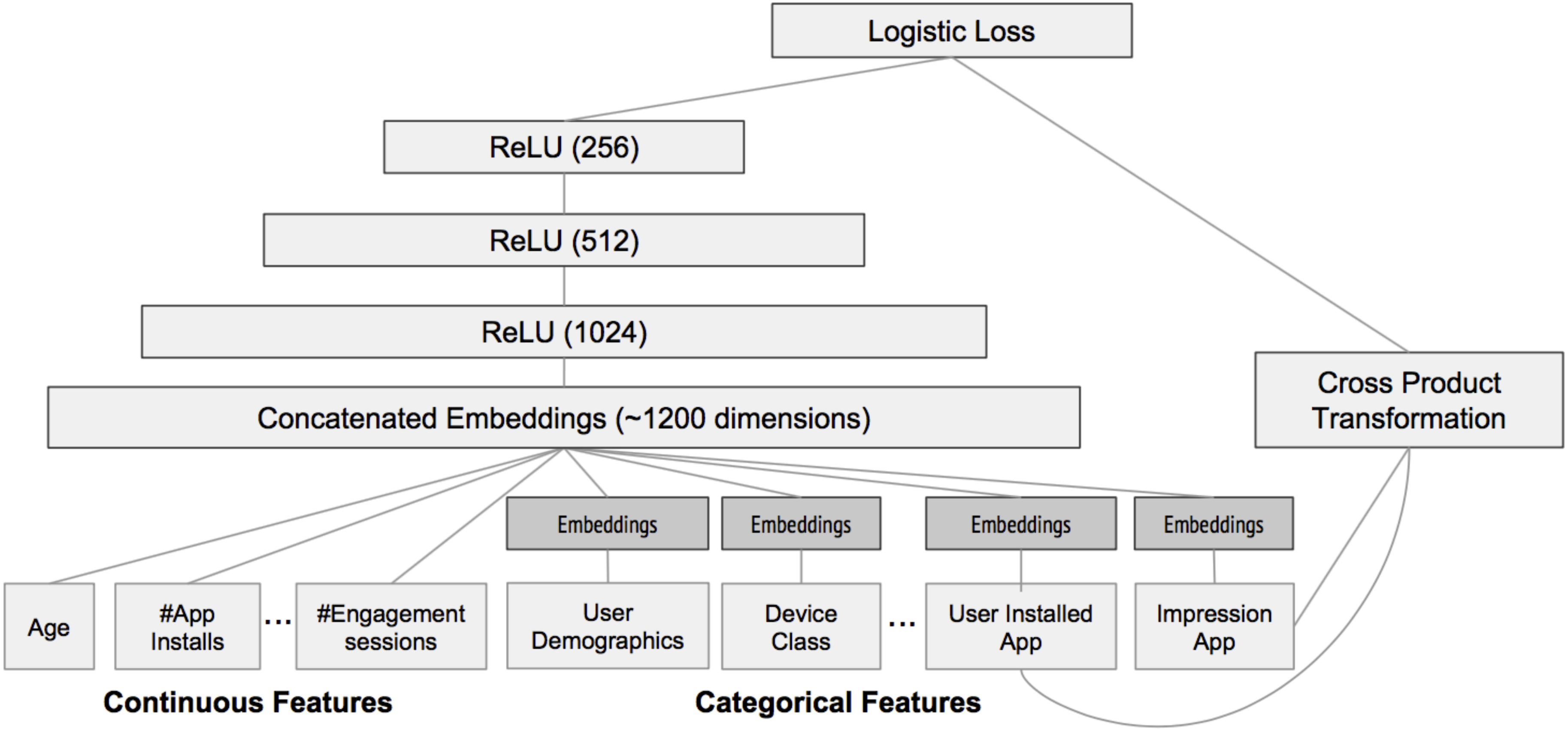
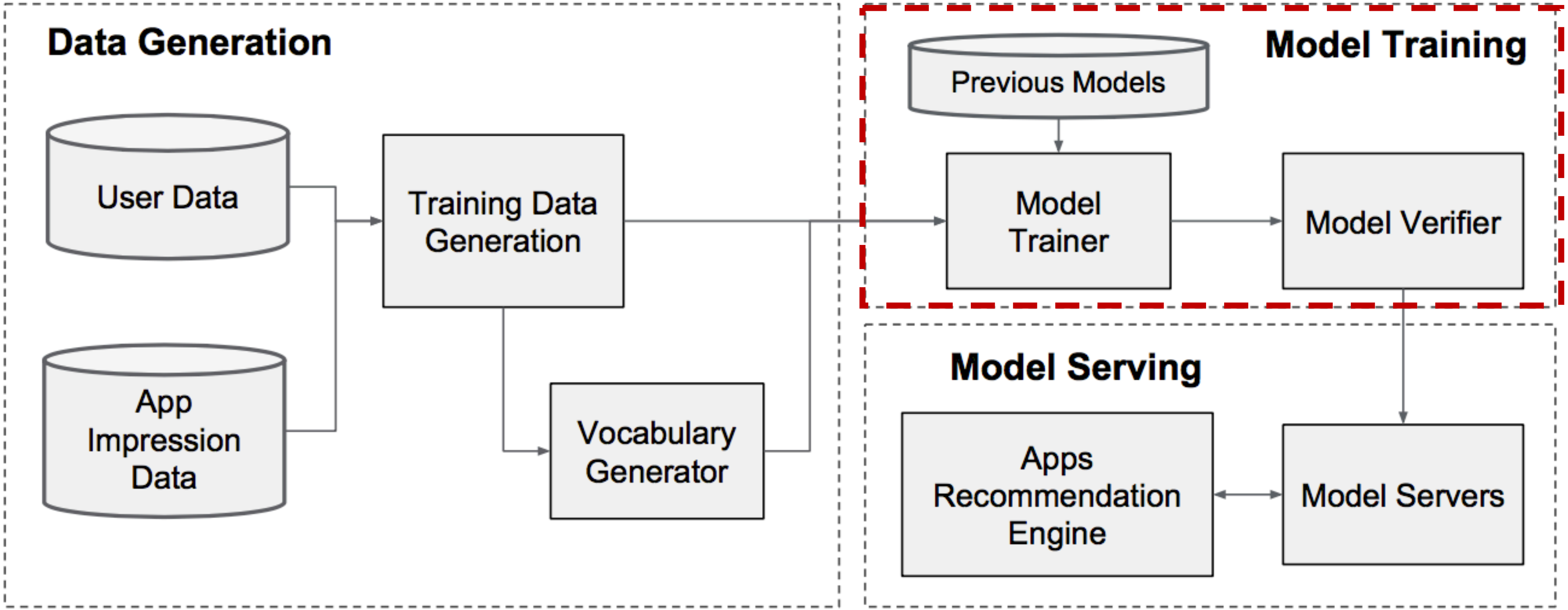


Logistic Loss
ReLU (256)
ReLU (512)
ReLU (1024)
Concatenated Embeddings (~1200 dimensions)
Cross Product Transformation
Embeddings
Embeddings
Embeddings
Embeddings
Age
#App Installs
...
#Engagement sessions
User Demographics
Device Class
...
User Installed App
Impression App
Continuous Features
Categorical Features

Wide & Deep



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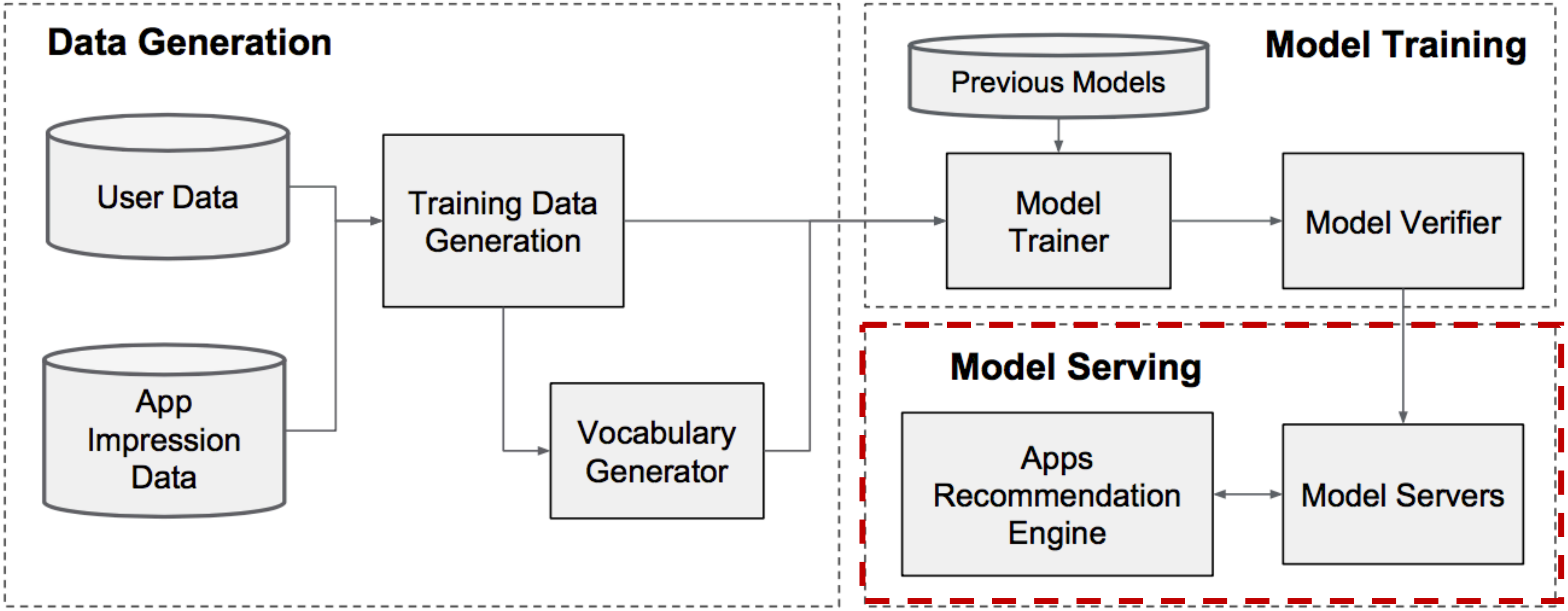
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Deep and Wide Notebook

- Demonstrate how to use the tf.esimator API to train a wide linear model and a deep feed-forward neural network.

The Goal

- Our Goal is to predict the rating category for a given pair of user id and movie id

	gender	age_desc	occ_desc	title	genre	rating	prediction	rating1	rating2	rating3	rating4	rating5
223742	M	35-44	clerical/admin	Little Princess, The (1939)	Children's|Drama	4	4	0.025210	0.068422	0.234015	0.375578	0.296774
915512	M	25-34	unemployed	Misery (1990)	Horror	4	3	0.105347	0.148656	0.290903	0.287796	0.167298
209015	M	25-34	technician/engineer	Supercop (1992)	Action|Thriller	3	4	0.050473	0.120541	0.292055	0.350531	0.186400
719570	M	25-34	other or not specified	Red Violin, The (Le Violon rouge) (1998)	Drama|Mystery	3	4	0.057457	0.115074	0.279706	0.332208	0.215554
283590	M	35-44	programmer	Manon of the Spring (Manon des sources) (1986)	Drama	4	4	0.025996	0.079624	0.237717	0.393170	0.263494

DnW Accuracy: 34.907003%

Implementation Steps

- Data preprocessing
- Build inputs
- Hash categorical features
- Create embeddings of sparse features for the deep model
- Define features for both the deep and the wide part of the model
- Train and validate the model

Big chunk !

Preparing the inputs

```
model =
tf.contrib.learn.DNNLinearCombinedClassifier(......
    )
```

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- Recommender Systems 101
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- Deep Matrix Factorization

Deep Matrix Factorization Notebook

- Demonstrate how to use the tensorflow lower API to build a DNN model from scratch.

The Goal

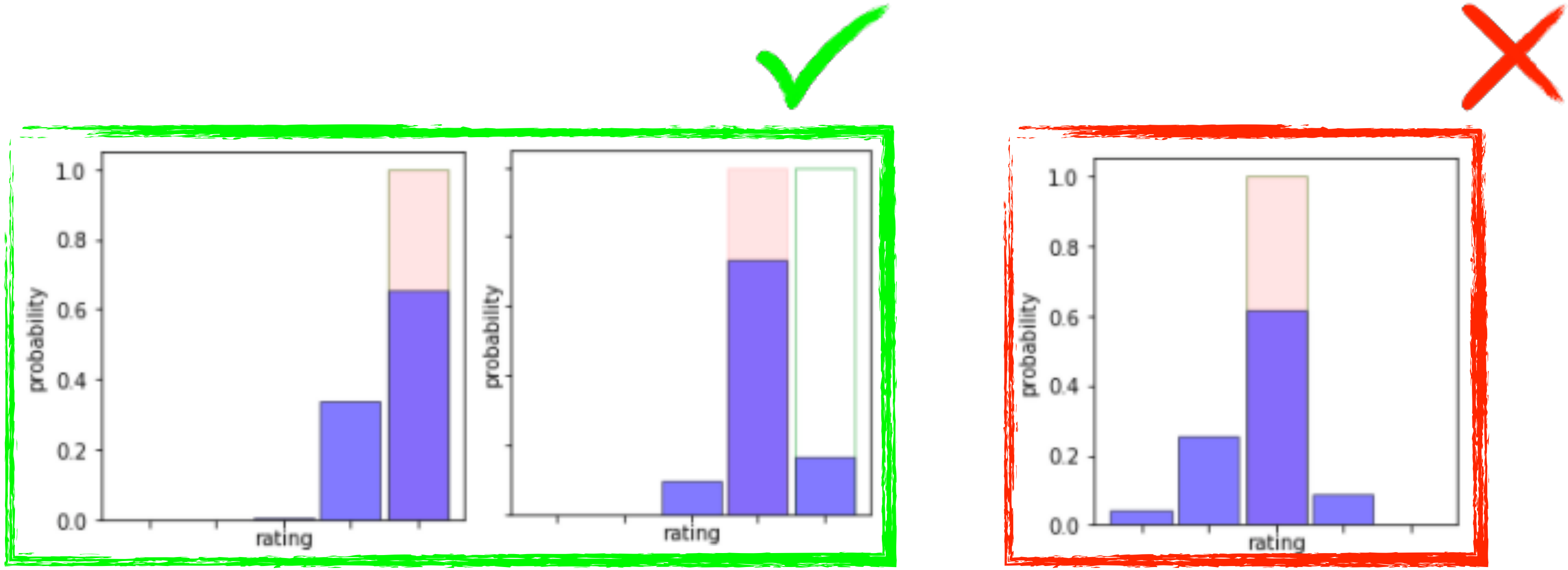
- Our Goal is not only to get a single prediction value, but also to know the probability distribution of the prediction.

	gender	age_desc	occ_desc	title	genre	rating	prediction	rating 1	rating 2	rating 3	rating 4	rating 5
690811	M	35-44	college/grad student	Ravenous (1999)	Drama|Horror	4	3	3.967836e-03	0.053077	0.484498	0.420719	0.037738
838395	M	56+	retired	Miss Julie (1999)	Drama	4	3	4.872613e-03	0.055875	0.457305	0.434597	0.047350
228947	M	25-34	sales/marketing	2001: A Space Odyssey (1968)	Drama|Mystery|Sci-Fi|Thriller	5	4	6.138799e-05	0.001535	0.041855	0.509231	0.447319
555611	M	Under 18	K-12 student	Saving Private Ryan (1998)	Action|Drama|War	5	5	2.225889e-08	0.000003	0.000494	0.102754	0.896749
745274	F	25-34	sales/marketing	Iron Giant, The (1999)	Animation|Children's	4	4	1.565472e-06	0.000149	0.016105	0.543688	0.440055

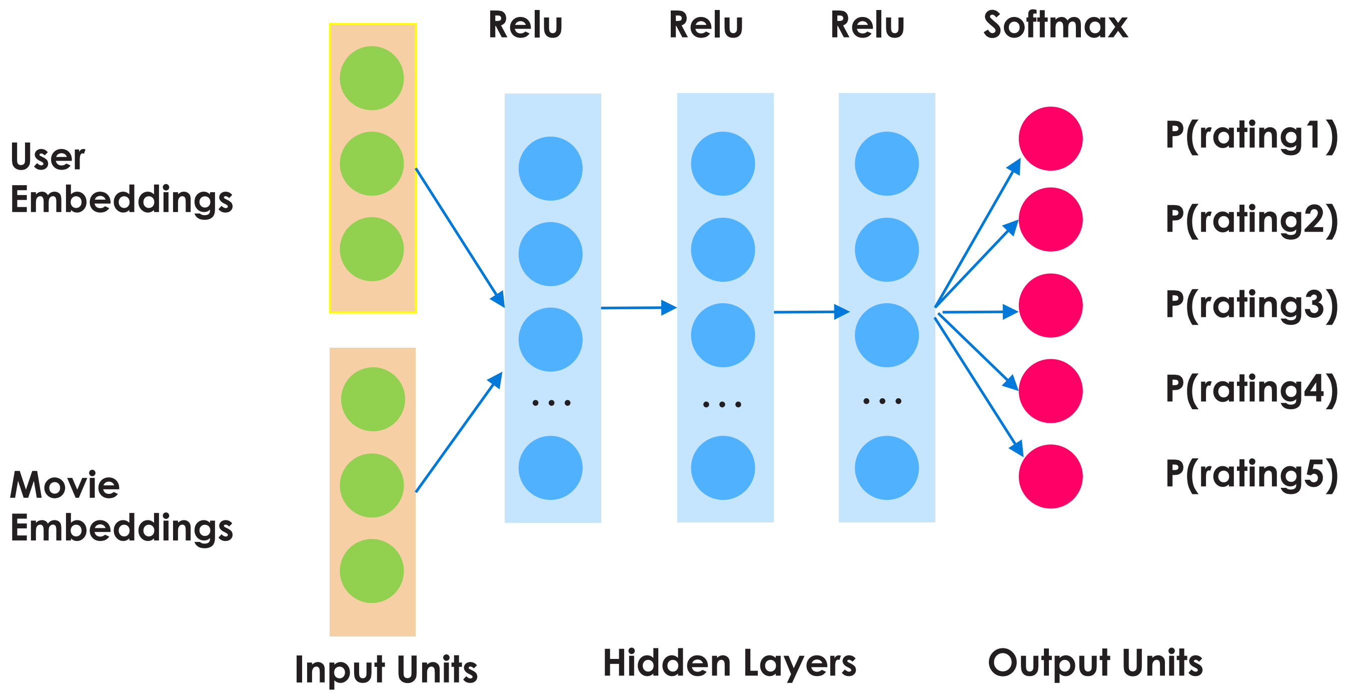
DNN Accuracy: 50.559383%

The Advantage

- With this additional probability information we can assess the risks and certainty of our result.

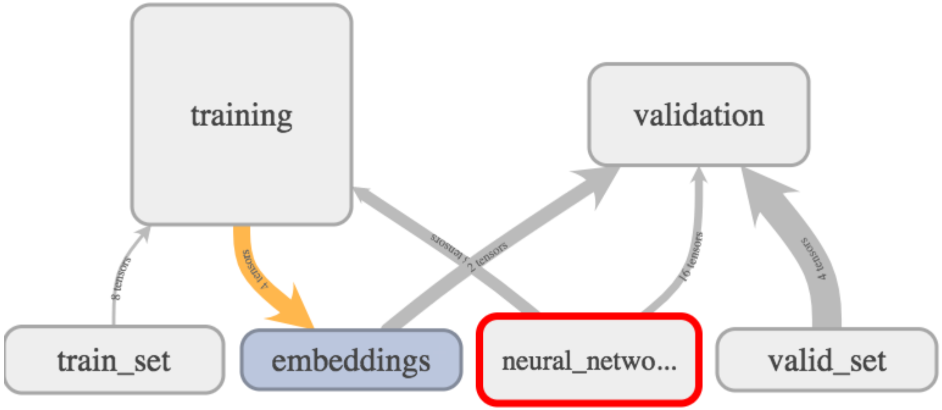


The Model


Relu
Relu
Relu
Softmax
User Embeddings
Movie Embeddings
P(rating1)
P(rating2)
P(rating3)
P(rating4)
P(rating5)
Input Units
Hidden Layers
Output Units

Implementation Steps

- Initialize the movie and user embeddings with the results trained in MF model
- Initialize the DNN parameter W and b
- Calculate Z n
- Calculate the prediction
- Calculate the loss
- Train and validate the model



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