

# Recommendation Systems || Lecture 8

University of Washington  
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July 25, 2022

# Logistics

- 1 Assignment 2 due wednesday night
- 2 Project deliverables doc up on canvas - Breakdown of project to help you stay on track!  
(syllabus)
- 3 Assignment 3 will be assigned wednesday and you get 2 weeks

Low not going down ] → Tomorrow noon  
(RMSE is high)

↳ Last assignment  
(Kaggle Contest)  
News Pecs

# Project Deliverables

- 1 **Baseline Model:** For your project, try couple of baseline models such as truncated SVD, etc
- 2 **Neural Network Model:** Try at least one NN model - E.g. AutoRec (AutoEncoder for Recommendations) or DeepRec or MLP (Multi-layer perceptron), etc
- 3 **Report:** Your report should be well formatted and organized just like a conference paper - With a) Abstract b) Introduction c) Reference to literature d) Your unique contribution in the paper e) Description of models used f) Description of data sets g) Description of metrics and key results comparing different models over the metrics (use a table for this) h) Conclusions and scope for future work
- 4 **Code:** Publish your complete code on github and link to it in the report. Keep your code organized (modular, use of classes, etc)
- 5 **Presentation:** One presentation per team (Unit tests)

# Project Timeline

- 1 **July 29:** Finish your 1:1 review of the project proposal

# Project Timeline

- ① **July 29:** Finish your 1:1 review of the project proposal
- ② **August 8:** Checkpoint for project - Submit baseline models, results  
and code | Report

# Project Timeline

- 1 **July 29:** Finish your 1:1 review of the project proposal
- 2 **August 8:** Checkpoint for project - Submit baseline models, results and code
- 3 **August 10:** Assignment 3 deadline



Assignment 3 deadline

# Project Timeline

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- 3 **August 10:** Assignment 3 deadline
- 4 **August 17:** Final project presentation (10 minutes per team)

↳ Last Lecture

# Project Timeline

- 1 **July 29:** Finish your 1:1 review of the project proposal
- 2 **August 8:** Checkpoint for project - Submit baseline models, results and code
- 3 **August 10:** Assignment 3 deadline
- 4 **August 17:** Final project presentation (10 minutes per team)
- 5 **August 19:** Neurips style white paper submission (check Neurips conference page for details)

↳ taken format for conference paper



# Project Timeline

- 1 **July 29:** Finish your 1:1 review of the project proposal
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- 3 **August 10:** Assignment 3 deadline
- 4 **August 17:** Final project presentation (10 minutes per team)
- 5 **August 19:** *Neurips style* white paper submission (check [Neurips conference page](#) for details)
- 6 **August 19:** Final code submission and link to [github project](#).

# Today!

- 1 Industry Case Study on Recommendations

# ICE #1

Let's say you have a loss function  $l(X, y; \theta)$  where  $X, y$  is the data and  $\theta$  are the parameters. You want to optimize (minimize) the loss for  $\theta$ . You take the gradient of the loss  $l$  at the current point,  $\theta^1$ . What does the direction of the gradient point to?

- 1 Direction of steepest ascent
- 2 Direction of steepest descent
- 3 It's just a collection of partial derivatives. Can't really attribute meaning to it.
- 4 None of the above



# Case Study: Stocking your Pantry



← Variety



Mangoes and Chutney

# Case Study: Online Pantry

amazon Prime Pantry

Departments - | Browning History - | Inf's Amazon.com | Today's Deals | Gift Cards & Registry | Sell | Help

EN | Hello, Inf | Account & Lists - | Orders | Prime - | Cart

PrimePantry | Order within 18 hrs 19 mins, get it by **Wednesday, May 10** | 1 box | 0 items | 0% full

Food | Beverages | Household & Pets | Beauty & Grooming | Wellness & Healthcare | Coupons & Deals | About Pantry

Add 5 qualifying items and get FREE shipping | [View all qualifying items >](#)

**Stock up for spring**  
Spend \$30, save \$5 and get free shipping  
Shop now >

EASY REORDER | NEW IN PANTRY | COUPONS | DEALS | ABOUT PANTRY

**Best Sellers in Prime Pantry** | Page 1 of 4

Product	Price	Rating	Quantity	Action
Nestlé Pure Life Purified Water, 16.9-ounce plastic	\$2.48 (\$0.01/Fl Oz)	★★★★☆ (652)	Fills 31.2% of your box (7)	Add to Cart
Ritz Crackers Sandwiches, Peanut Butter, 6-1.38	\$2.78 (\$0.25/Ounce)	★★★★☆ (295)	Fills 1.8% of your box (7)	Add to Cart
Heinz Tomato Original Ketchup, 32 Ounce Bottle	\$2.88 (\$0.09/Ounce)	★★★★☆ (697)	Fills 4.8% of your box (7)	Add to Cart
Dole Fruit Bowls, Mandarin Oranges in	\$2.42 (\$0.15/Ounce)	★★★★☆ (251)	Fills 2.8% of your box (7)	Add to Cart
Kraft Macaroni & Cheese Dinner Cups, Original,	\$3.01 (\$0.37/Ounce)	★★★★☆ (1,055)	Fills 3% of your box (7)	Add to Cart
Oreo Double Stuf Chocolate Sandwich	\$2.98 (\$0.19/Ounce)	★★★★☆ (809)	Fills 2.4% of your box (7)	Add to Cart
Kleenex Ultra Soft & Strong Facial Tissues, 75	\$6.59 (\$0.02/Count)	★★★★☆ (338)	Fills 5.8% of your box (7)	Add to Cart
Ultra Downy Asri Fresh Liquid Fabric Softener	\$8.38 (\$0.07/load)	★★★★☆ (451)	Fills 15.8% of your box (7)	Add to Cart

# Discovery and Browsing



Snyder's of Hanover 100 Calorie Pretzels Variety Pack, 19.8 Ounce by Snyder's of Hanover

\$6<sup>53</sup> (\$0.33/Ounce) *PrimePantry*

Exclusively for Prime Members  
Fills 16.4% of your Pantry box (?)

★★★★☆ 92

1 ▾ Add to Cart



KIND Healthy Grains Granola Bars, Oats and Honey with Toasted Coconut, Gluten Free, 1.2 oz Bars, 5 Count by KIND

\$3<sup>15</sup> (\$0.51/Ounce) *PrimePantry*

Exclusively for Prime Members  
Fills 1% of your Pantry box (?)

★★★★☆ 79

1 ▾ Add to Cart



Nature Valley Biscuits, Almond Butter, Breakfast Biscuits with Nut Filling, 5 Bars - 1.4 oz by Nature Valley

\$2<sup>50</sup> (\$0.50/Count) *PrimePantry*

Exclusively for Prime Members  
Only 4 left in stock - order soon.  
Fills 1.2% of your Pantry box (?)

★★★★☆ 102

1 ▾ Add to Cart



Wheat Thins Crackers, Reduced Fat, 14.5-Ounce Box (Packaging vary) by Wheat Thins

\$3<sup>88</sup> (\$0.27/oz) *PrimePantry*

Exclusively for Prime Members  
Fills 2.6% of your Pantry box (?)

★★★★☆ 84

1 ▾ Add to Cart

◀ Previous Page

1 2 3 ... 37

Next Page ▶

# Recommendations are not basket oriented

Larabar Gluten Free Bar, Blueberry Muffin, 1.6 oz Bars (5 Count) by LÄRABAR  
★★★★☆ 154 customer reviews | 2 answered questions



Customers who bought this item also bought

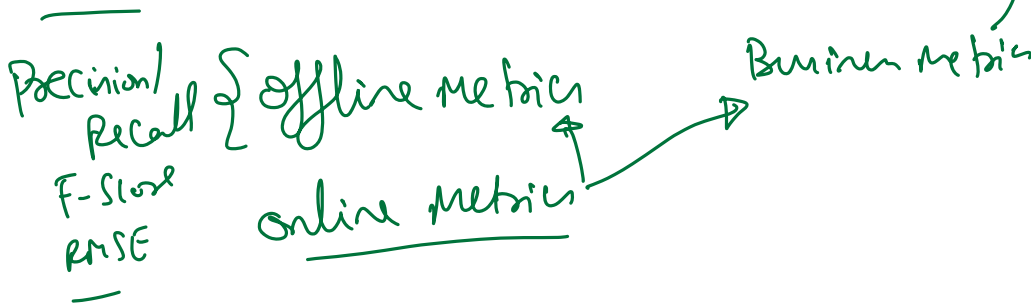
Product Name	Price	Rating
Larabar Fruit & Nut Food Bar Gluten Free Non-GMO Apple Pie 1.6 oz Bar (5 Count)	\$4.98 PrimePantry	★★★★☆ 129
Larabar Gluten Free Bar, Chocolate Chip Cookie Dough, 1.6 oz Bars (5 Count)	\$4.98 PrimePantry	★★★★☆ 87
Larabar Gluten Free Bar, Cashew Cookie, 1.7 oz Bars (5 Count)	\$4.98 PrimePantry	★★★★☆ 25
Larabar Gluten Free Bar, Peanut Butter Chocolate Chip, 1.6 oz Bars (5 Count)	\$4.98 PrimePantry	★★★★☆ 80
Larabar Gluten Free Bar, Peanut Butter Cookie, 1.7 oz Bars (5 Count)	\$4.99 PrimePantry	★★★★☆ 61

# Business problem

Make it easier for a customer to fill a basket with a personalized carousel of relevant and diverse products.

How to measure?

- Increase in units purchased per order
- Decrease in cart abandonments



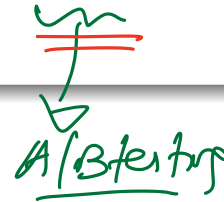


# Contributions

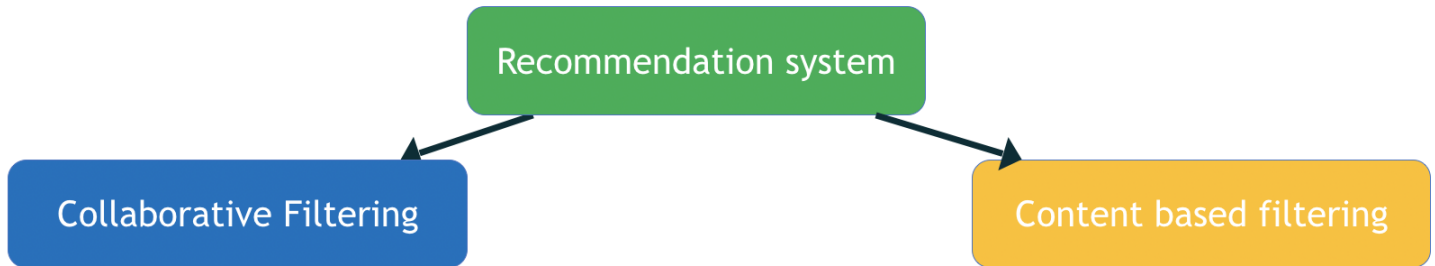
- **Provide** a joint relevance and diversity model for personalized basket recommendations
- **Demonstrate** the effectiveness of this model in online and offline experiments



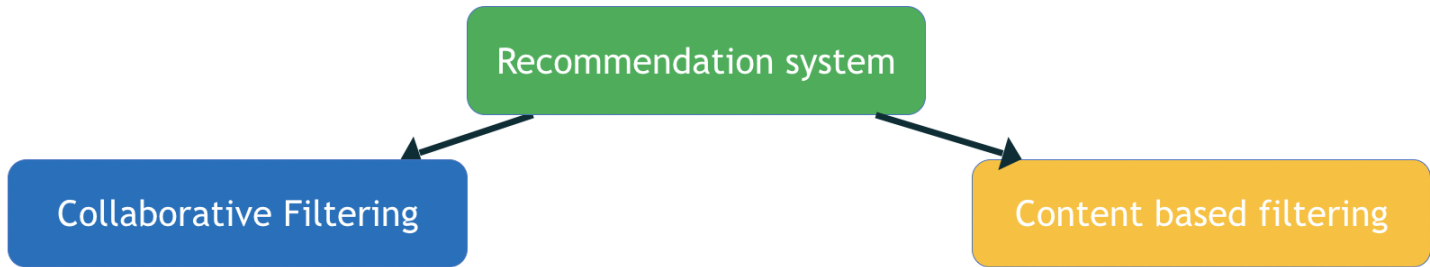
A/B test  
A - Control → webpage has no changes  
B - Treatment → You change in the webpage



# Traditional Recommendation Systems



# Traditional Recommendation Systems







(Behavior)

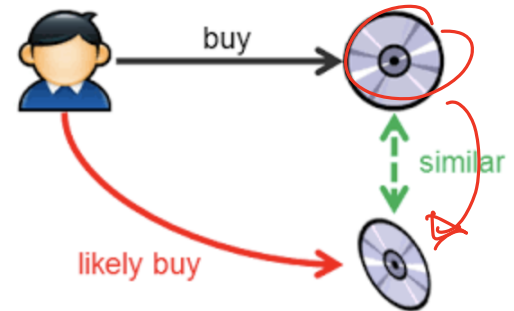
# Traditional Recommendation Systems

Recommendation system

Collaborative Filtering

Content based filtering

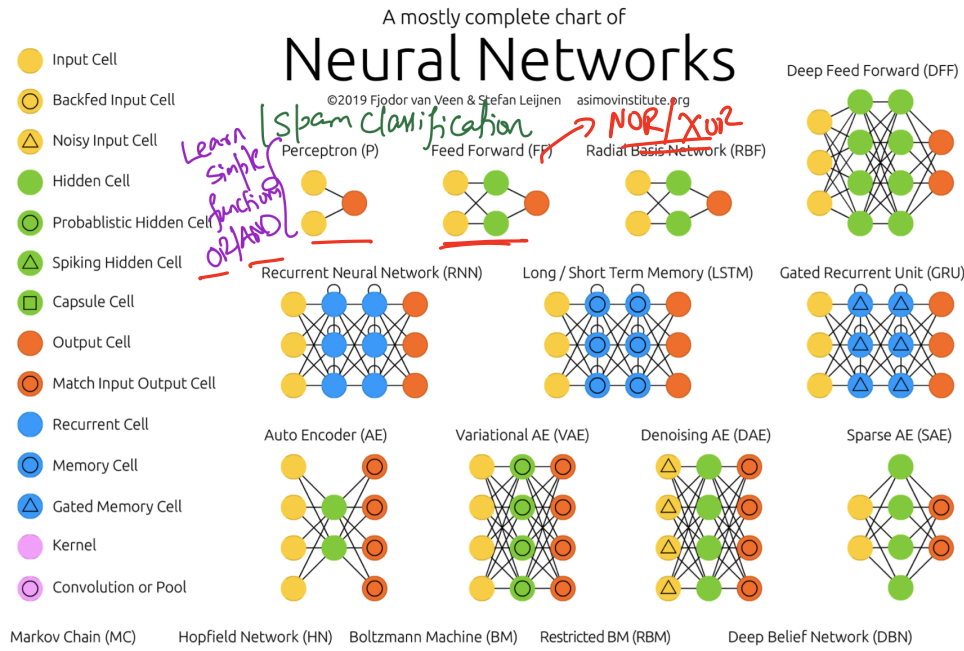


# Deep Learning for Recommendation Systems

- YouTube
- Netflix
- Yahoo News
  
- Amazon Videos
- Pantry Basket recommendations
- Fresh recommendations
- More!?

# Quick tour of DL Architectures

## Neural Networks Zoo



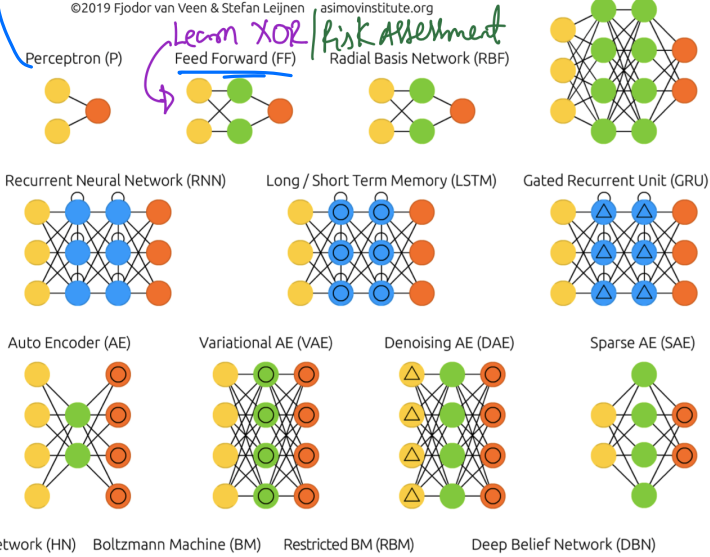
# Quick tour of DL Architectures

## Neural Networks Zoo

- Input Cell
- Backfed Input Cell
- △ Noisy Input Cell
- Hidden Cell
- Probabilistic Hidden Cell
- △ Spiking Hidden Cell
- Capsule Cell
- Output Cell
- Match Input Output Cell
- Recurrent Cell
- Memory Cell
- △ Gated Memory Cell
- Kernel
- Convolution or Pool

### A mostly complete chart of Neural Networks

©2019 Fjodor van Veen & Stefan Leijnen asimovinstitute.org



*Linear Regression (Linear Decision boundary)*

*Decision boundary is non-linear*

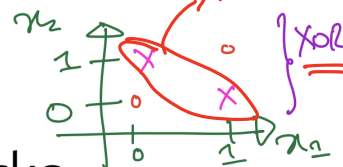
*Linear XOR Risk Assessment*

*Perceptron (P)*

*Feed Forward (FF)*

*Radial Basis Network (RBF)*

*Deep Feed Forward (DFF)*



# Quick tour of DL Architectures

## Neural Networks Zoo

- Input Cell
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- Kernel
- Convolution or Pool

### A mostly complete chart of Neural Networks

©2019 Fjodor van Veen & Stefan Leijnen [asimovinstitute.org](http://asimovinstitute.org)

*Recommender System / Classification*

Deep Feed Forward (DFF)

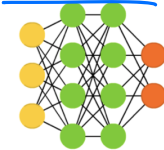
Perceptron (P)



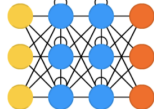
Feed Forward (FF)



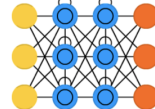
Radial Basis Network (RBF)



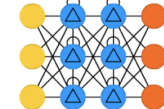
Recurrent Neural Network (RNN)



Long / Short Term Memory (LSTM)



Gated Recurrent Unit (GRU)



Auto Encoder (AE)



Variational AE (VAE)



Denosing AE (DAE)



Sparse AE (SAE)



Markov Chain (MC)

Hopfield Network (HN)

Boltzmann Machine (BM)

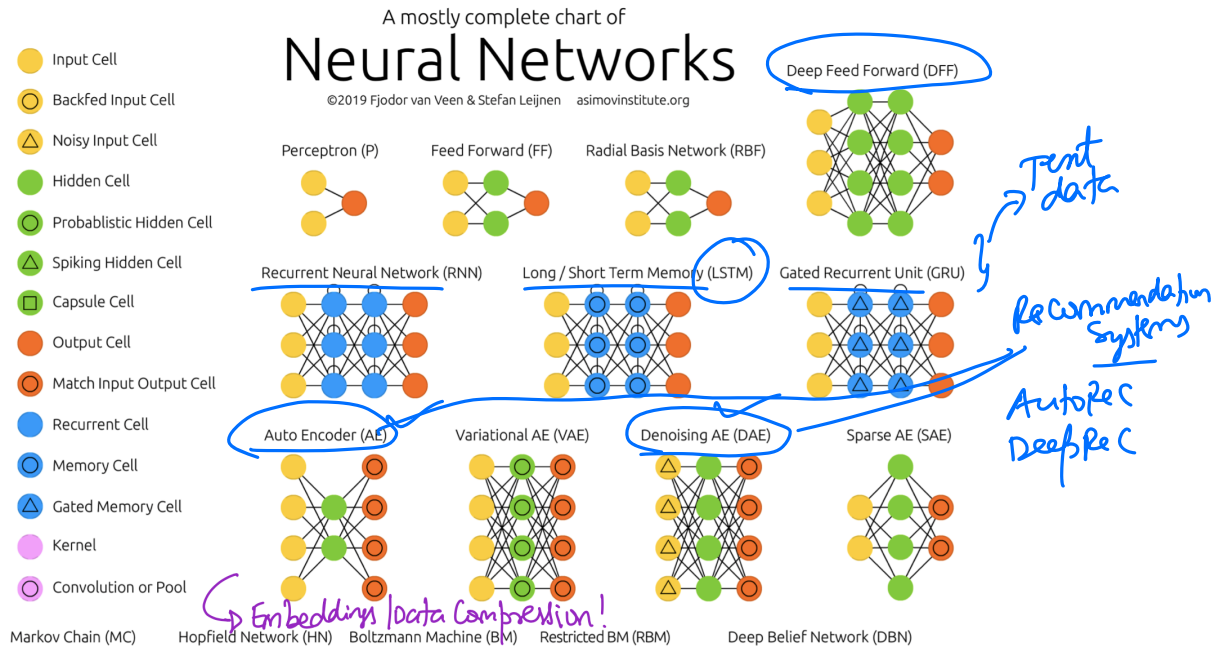
Restricted BM (RBM)

Deep Belief Network (DBN)



# Quick tour of DL Architectures

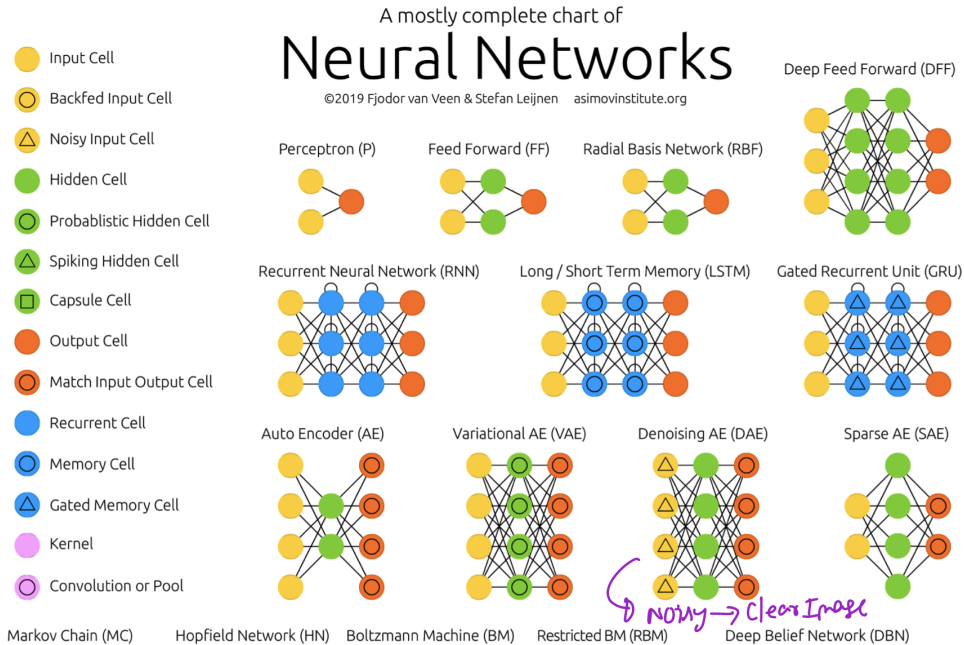
## Neural Networks Zoo



# Quick tour of DL Architectures

## Neural Networks Zoo

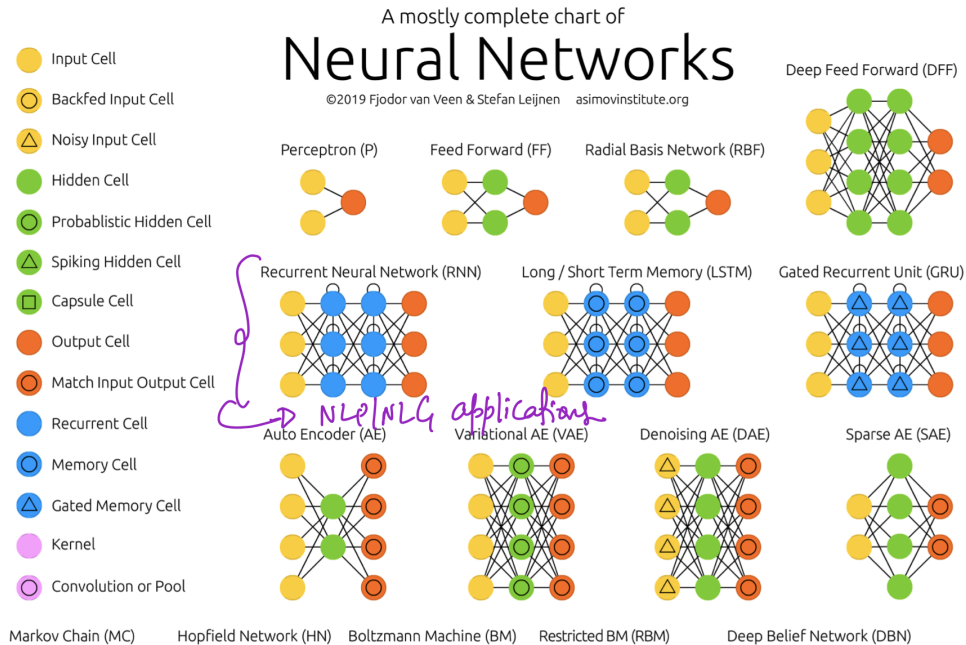
### Neural Networks Zoo



# Quick tour of DL Architectures

## Neural Networks Zoo

### Neural Networks Zoo



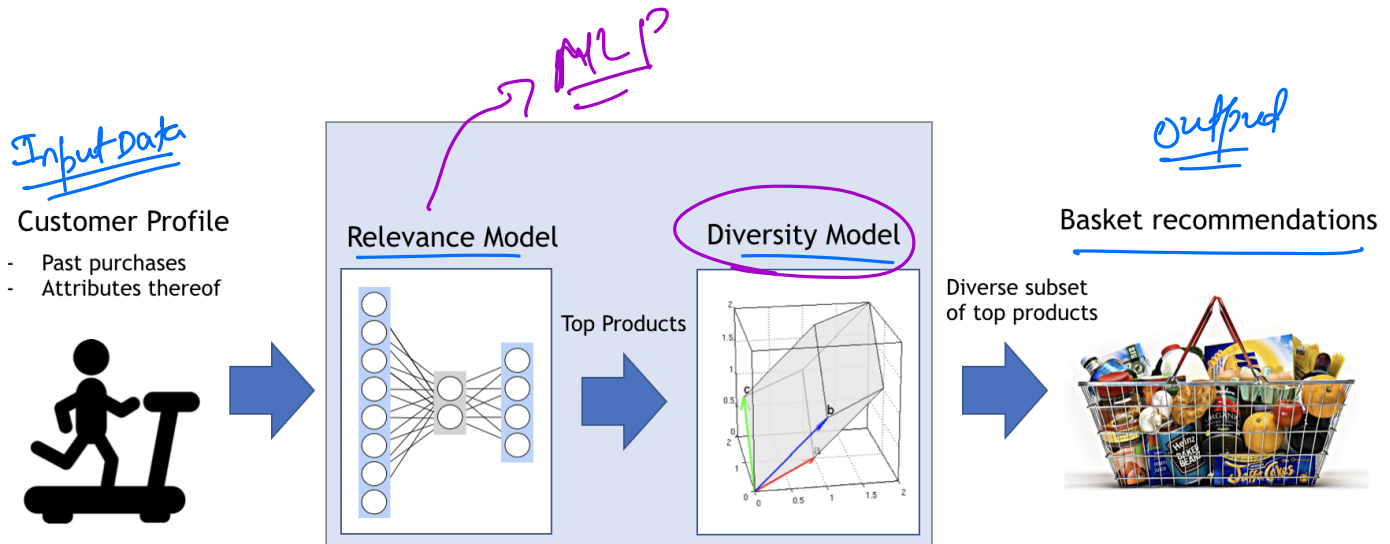
# Deep Learning for Recommendation Systems

- Auto-Encoders (Non-linear MF) ✓
- Multi-layer perceptron (MLP) [YouTube] (FSN) → Today!
- Deep semantic structured models (DSSM) (next Lec)
- Sequence models based on RNN (recs within session) (next Data)
- Other models (e.g. wide and deep learning) [Google]

# Deep Learning for Recommendation Systems

- Auto-Encoders (Non-linear MF)
- Multi-layer perceptron (MLP)
- Deep semantic structured models (DSSM)
- Sequence models based on RNN (recs within session)
- Other models (e.g. wide and deep learning) [1]

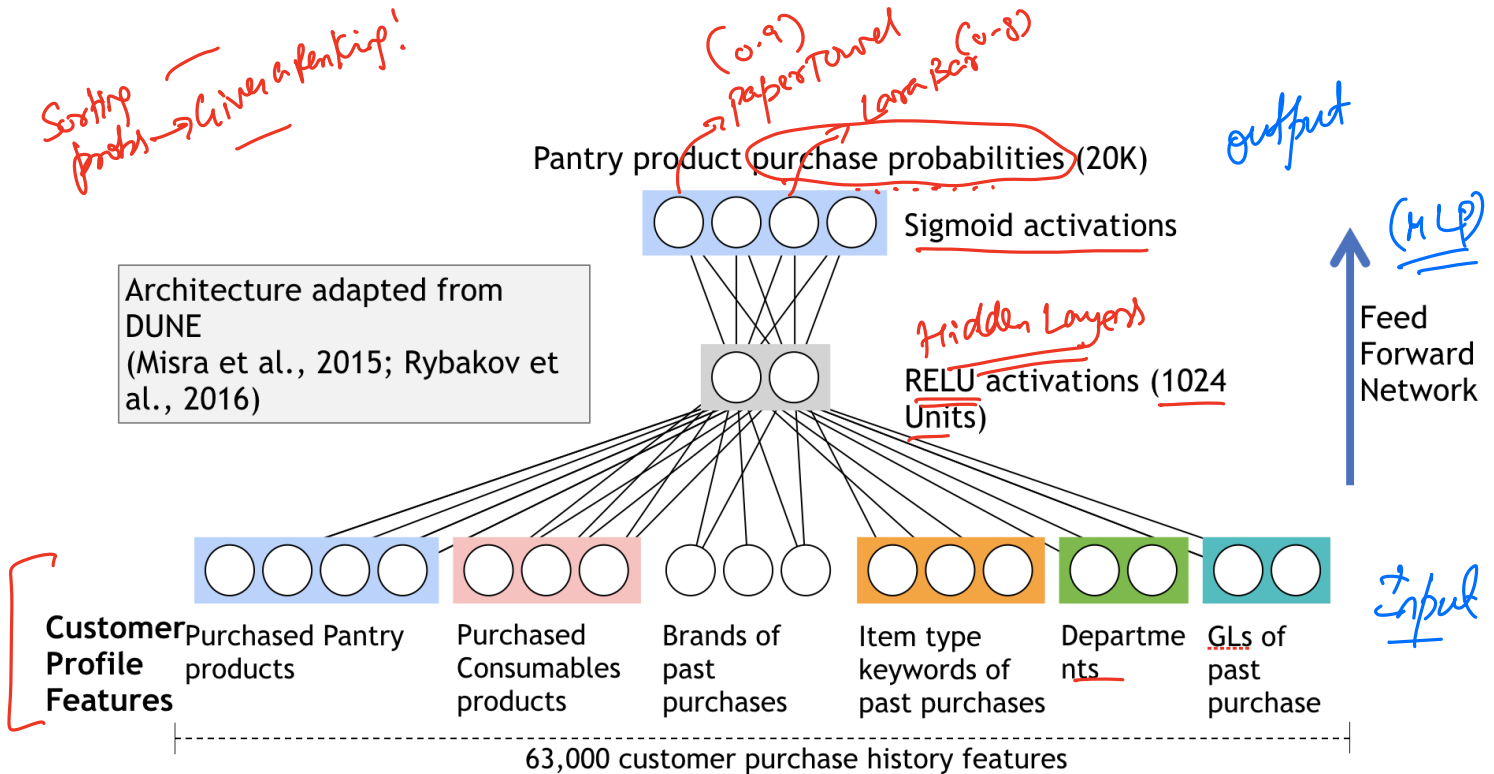
# Joint Relevance and Diversity Model for Pantry Recommendations



Balancing relevance and diversity for prime pantry recommendations. Mohan et al. AMLC 2017

# Relevance Model

# Relevance Model



Input  $\rightarrow$  BOW (0/1 & 1/1)



## Precision @ K vs Precision

Recs  
1 3 5  
 ↑ ↑  
 ProductIds

Purchase (Truth)  
1 5 4 9  
 ↑ ↑  
 ProductIds

$$\text{Precision} = \frac{\text{Recs} \cap \text{Purchase}}{|\text{Recs}|} = \frac{2}{3}$$

$$\text{Recall} = \frac{\text{Recs} \cap \text{Purchase}}{|\text{Purchase}|} = \frac{2}{4}$$

$$\text{Precision@2} = \frac{1}{2}$$

$$\text{Recall@2} = \frac{1}{4}$$

Precision High, Recall is Low  $\Rightarrow$  Model is not having coverage

E.S.

Recs  
1 3

Purchase  
1 3 5 7 9 10 11 15

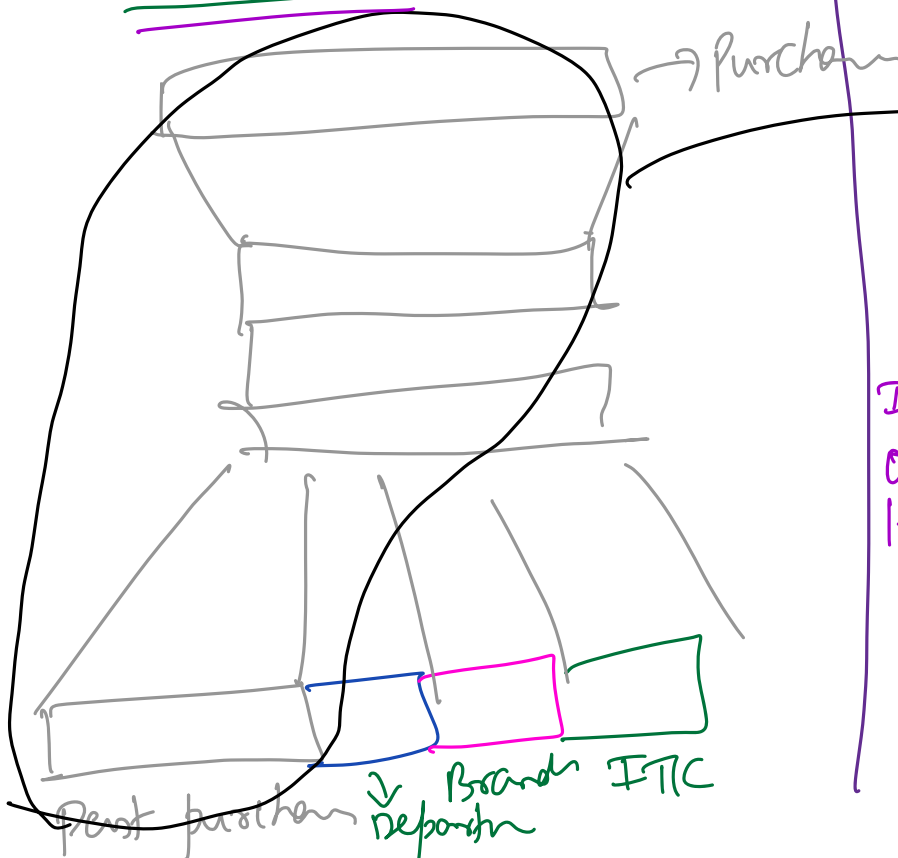
$$\text{Precision} = \frac{2}{2} = 100\% \quad (\text{Accuracy})$$

$$\text{Recall} = \frac{2}{8} = 25\% \quad (\text{Coverage})$$

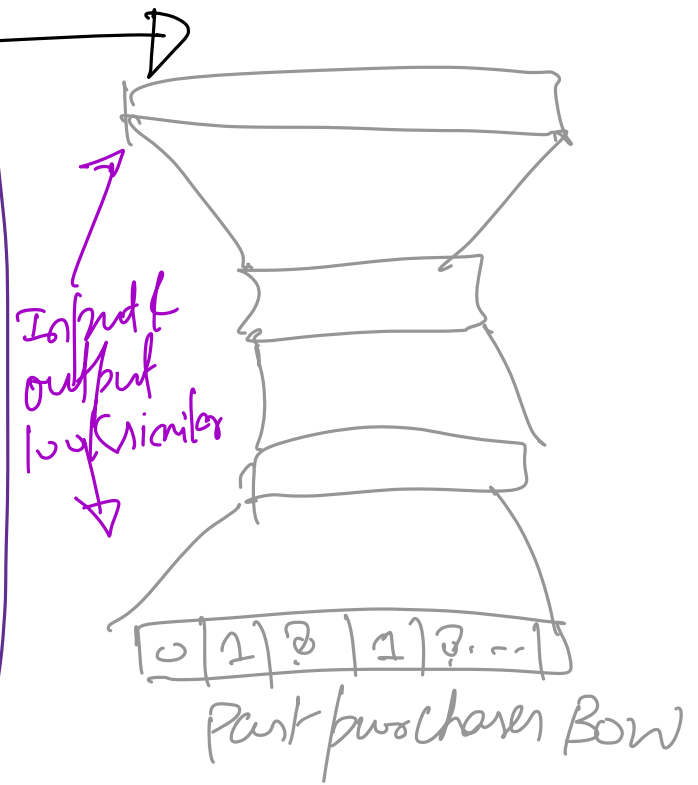
$$\text{F-Score} = \frac{2PR}{P+R} \quad (\text{Harmonic mean})$$

# MLP vs AutoEncoder (AutoRec)

MLP (FFN)



AutoRec



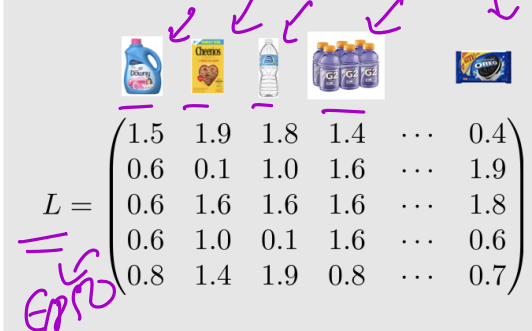
# Diversity Model

# Embeddings for Products

2D Represent



Represent products in product space with a large matrix of embedding coordinate vectors "L"



We obtain these embedding vectors from the Product2Vec service [London et al, 2017]

# Diversity Subset Selection through DPP

$S_{ij} \rightarrow$  Similarity between product  $i$  & product  $j$   
 $= L_i^T L_j$

Similarity matrix

Let  $L$  be the Product2Vec embeddings.  $S = L^T L$  is the similarity matrix of the asins.

Determinantal point processes (DPP)

DPP [3] is a probability distribution over subsets of a ground set.

$$\mathcal{P}(J) \propto \log(\det(S_J))$$

Diversity and DPP

DPP favors sets that are more diverse.

[2] London et al. Product2Vec: A multi-task learning framework for cold-start product recommendation. AMLC 2016

[3] Kulesza et al. Determinantal point process for machine learning. Foundations and trends in ML, 2012

# Visualizing Determinants

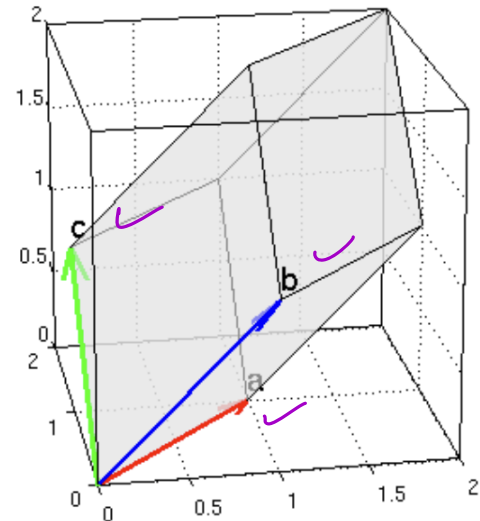
Larger the volume  $\Leftrightarrow$  more diversity!

Given product vectors  $\{ \mathbf{a}, \mathbf{b}, \mathbf{c} \}$  and matrix

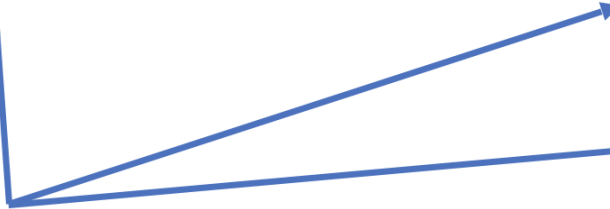
$$L = \begin{pmatrix} | & | & | \\ \mathbf{a} & \mathbf{b} & \mathbf{c} \\ | & | & | \end{pmatrix}$$

the determinant of  $LL^T$  is the squared volume of the parallelepiped.

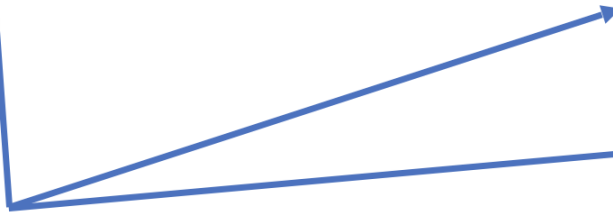
$$\det(\underline{LL^T}) = \underline{\text{Vol}^2}$$



# Diversity through Determinants



# Diversity through Determinants



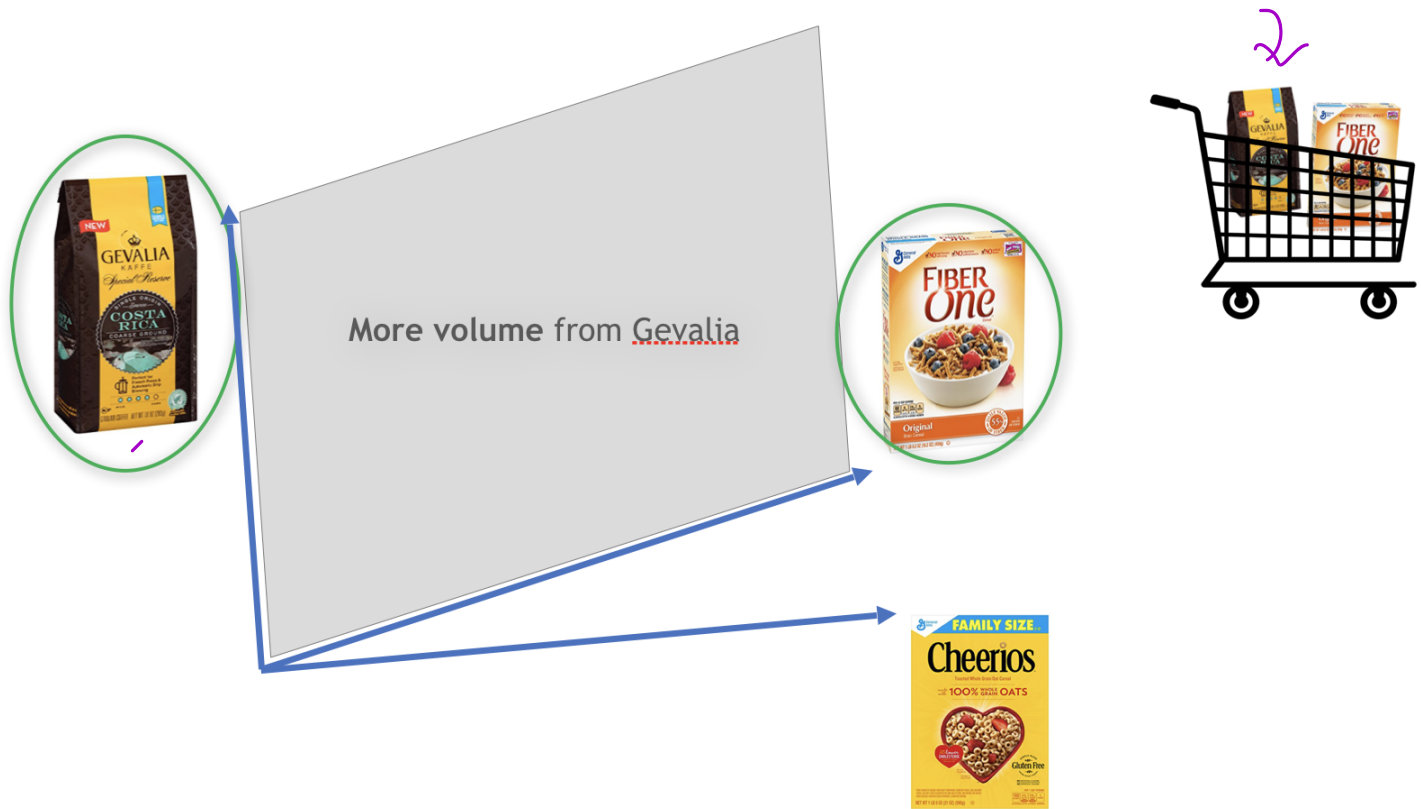


# Diversity through Determinants



Volume from adding cheerios

# Diversity through Determinants



# Trading-off Relevance and Diversity

Optimization objective strikes a balance

$$\max_{J:|J|=k} \sum_{j \in J} r_j$$

The  $r_j$  are scores from the relevance model

(prob. scores)

# Trading-off Relevance and Diversity

Optimization objective strikes a balance

$$\max_{J: |J|=k} \sum_{j \in J} r_j + \lambda \log \det \left( \sum_{j \in J} L_j L_j^T + \gamma \mathbf{I} \right)$$

*Trade-off parameter*

⏟

⏟

Diversity

The  $r_j$  are scores from the relevance model

log-det measures diversity of the set

# Trading-off Relevance and Diversity

Optimization objective strikes a balance

$$\max_{J:|J|=k} \sum_{j \in J} r_j + \lambda \log \det \left( \sum_{j \in J} L_j L_j^T + \gamma \mathcal{I} \right)$$

Trade-off parameter

Smoothing parameter

The  $r_j$  are scores from the relevance model

log-det measures diversity of the set

*Hyper-parameters*

# Optimizing the trade-off

## Hardness of mode-finding

Mode-finding in DPP is NP-hard [4]. Hence, maximizing the joint relevance-diversity objective is also NP-hard.

## Approximation algorithm

We provide a  $(1 - 1/e)$ -approximation algorithm to find the optimal sub-set of the joint relevance-diversity optimization problem.

# Greedy Algorithm for Subset Selection (GDPP)

Initialize

Initialize set  $\mathbf{J}$  with the most relevant ~~asin.~~

product

Iterate until  $|\mathbf{J}| = K$

- ▶ Pick asin  $j$  that has the appropriate balance between relevance and diversity:

$$j \leftarrow \arg \max_{k \notin \mathbf{J}} \left( r_k + \lambda \log \det(L_{\mathbf{J}}L_{\mathbf{J}}^T + L_kL_k^T + \gamma\mathbf{I}) \right)$$

- ▶ Add asin  $j$  to set  $\mathbf{J}$ .

# Greedy Algorithm for Subset Selection (GDPP)

## Initialize

Initialize set  $\mathbf{J}$  with the most relevant asin.

## Iterate until $|\mathbf{J}| = K$

- ▶ Pick asin  $j$  that has the appropriate balance between relevance and diversity:

$$j \leftarrow \arg \max_{k \notin \mathbf{J}} \left( \mathbf{r}_k + \lambda \log(1 + \underbrace{\mathbf{L}_k^T (\mathbf{L}_\mathbf{J} \mathbf{L}_\mathbf{J}^T + \gamma \mathbf{I})^{-1} \mathbf{L}_k}_{\text{Efficient computation via rank-1 updates}}) \right)$$

- ▶ Add asin  $j$  to set  $\mathbf{J}$ .

Relevance of ASIN  
 $k$

Efficient computation via  
rank-1 updates



# Greedy Algorithm for Subset Selection (GDPP)

## Theorem (GDPP approximation)

*GDPP enjoys a  $(1 - 1/e)$ -approximation guarantee in optimizing the joint relevance diversity objective.*

## Proof.

We note that the diversity part of the objective is submodular and monotone increasing. Since the relevance sum,  $\sum_{k \in J} r_k$  is modular and monotone increasing, the joint relevance-diversity objective is submodular and monotone increasing. The result thus follows from Nemhauser et al [4] □

Nemhauser et al. An analysis of approximation algorithms for maximizing submodular set functions. 1978.

# Diversity Algorithm Walkthrough

*Candidate products*

*Similar*

*Similar*



1



2



3



4



5



6



7



8



9



10

# Visualizing selection process

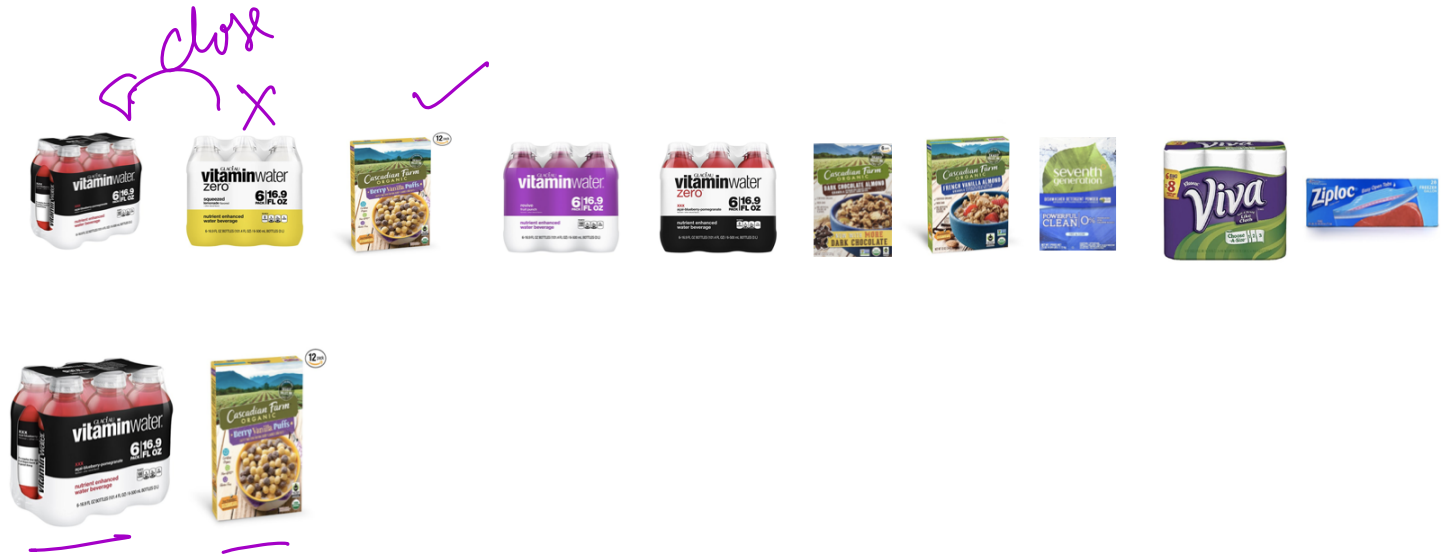


# Visualizing selection process



↑  
Most relevant  
product  
(1)

# Visualizing selection process



# Visualizing selection process



# Visualizing selection process



# Visualizing selection process





# Visualizing selection process



↓  
ShowCase to Customer  
—Relevant yet diverse!

# Free-shipping A/B test

- Prime Pantry charges \$5.99 per box ordered
- Pantry offers sponsored products which qualify customers for free shipping

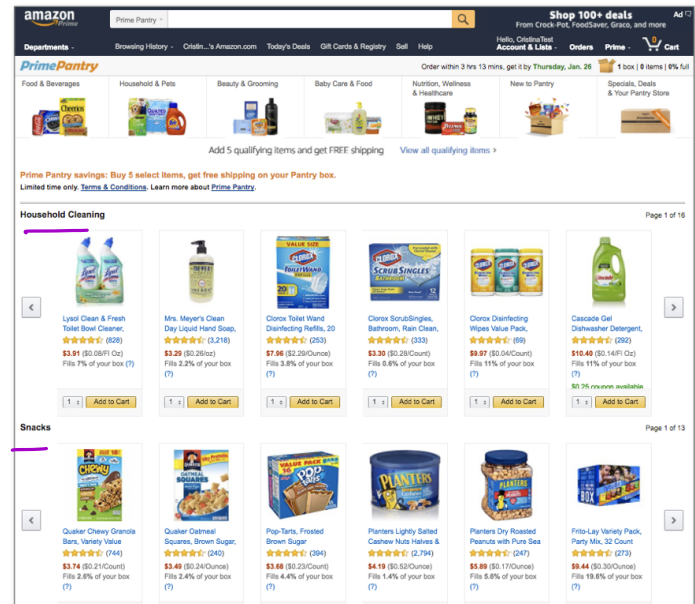
*“Buy 5 Select Items Get Free Shipping”*

- Help Prime Pantry customers find qualifying products through personalized recommendations

# Control

## Control Experience

- Free ship product carousels by category
- Categories ordered by popularity
- No personalized carousels



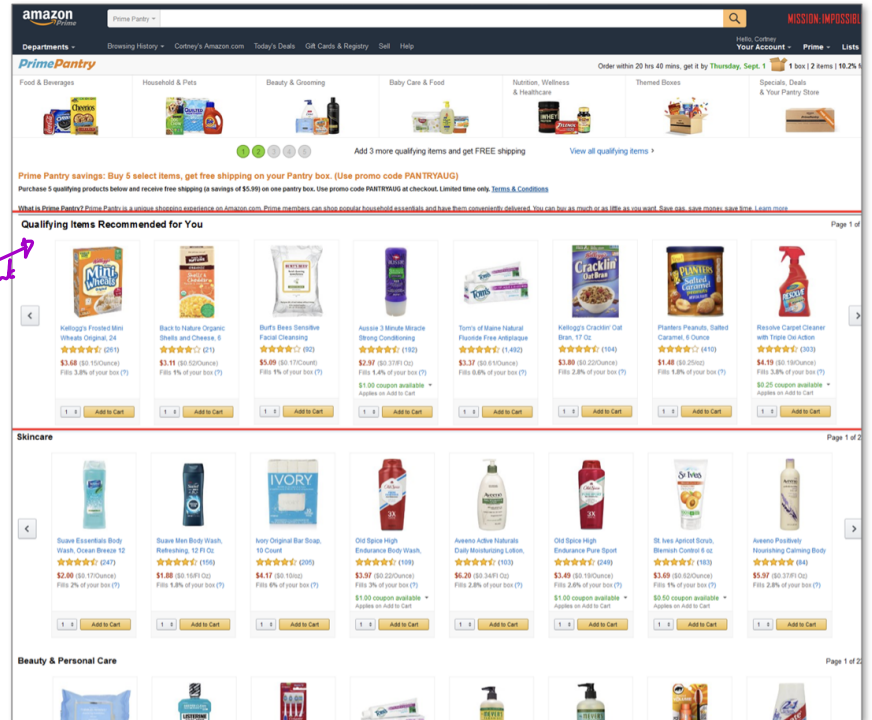
# Treatment

## Treatment

- Personalized carousel at the top of the page with qualifying items recommended by model

*“Qualifying Items Recommended for You”*

*fresh*



# A/B test outcome

Metric	Percentage change	P-value
Units metric	x% increase	0.001 *
Session metric	y% decrease	0.004 *
Pantry metric	z% increase	0.001 *

Business metrics

Statistical Significant

# Summary

- MLP/FFN (Extension of AutoRec)
- Relevance & Diverse Model (jointly)
- offline Testing (Train/Val/Test)  
& online Testing (A/B Test)
- Improvement in offline metrics  
Precision/Recall/F-score  
& business metrics

---

## Other facets

1. Training Schedule

2. Training Time Opt

3. Inference time optimization

4. Cold-Start Customers