From Risk to Profitability

Agenda

- **Introduction to Fischer Jordan**
- Analytics Evolution and Customer Life Cycle
- Leveraging Analytics across Customer Life Cycle

Introduction to Fischer Jordan

- **Analytics consulting firm specializing in financial services space**
- **Focus on leveraging analytics and technology to drive rapid bottom-line impact**
- **Provider-agnostic approach**

Agenda

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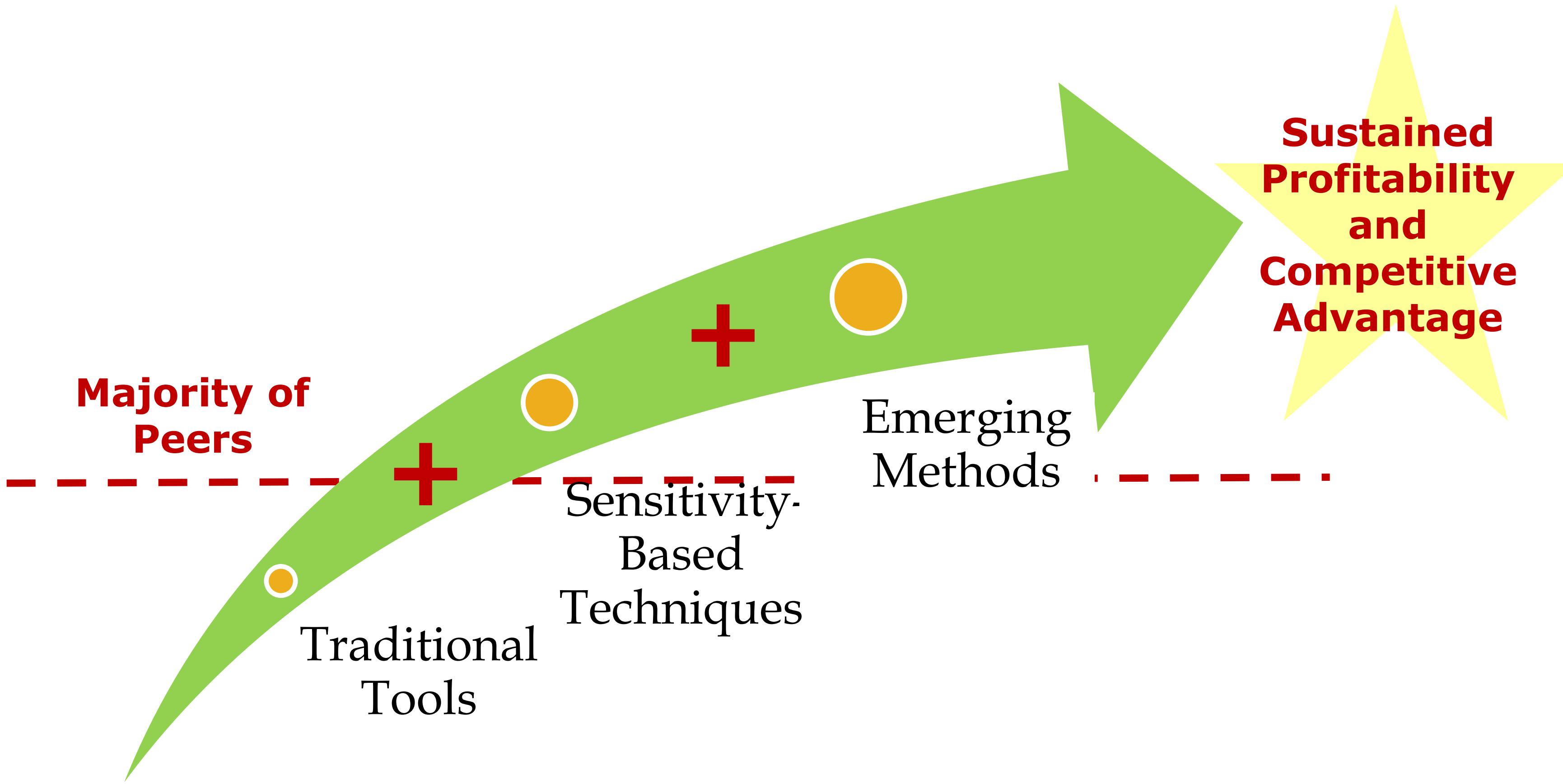
Analytics Evolution

Leveraging the wealth of information and advances in analytics is critical to maintaining competitive advantage



Customer Life Cycle

Advances in analytics find immediate applications across the life cycle

Applications across Customer Life Cycle

	Acquisition	Origination / Underwriting	Customer / Payment Management	Collections
Traditional	▪ Response and Approval Models and Segmentation	▪ Risk modeling and segmentation, collateral values prediction ▪ Customer Lifetime Value Optimization	▪ Risk modeling ▪ Cross-Sell and Up-sell campaigns	▪ Segmentations ▪ Payback likelihood, repossession and collateral value model
Sensitivity -Based	▪ Acquisition Pricing Optimization, Dealer Incentives	▪ Front- and Back-end approvals ▪ Pricing and dealer incentives optimization	▪ Default Pricing	▪ Population-based segmentation techniques used to optimize treatment strategy
Emerging	▪ Linking and matching ▪ Leveraging click-stream data in lead generation and conversion	▪ Online behaviors		

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- **Leveraging Analytics across Customer Life Cycle**

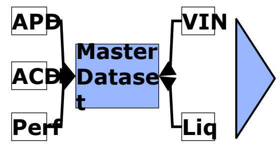
Case 1: Enhancing Front-End Approval Decisions

Traditional tools, when properly used still unlock a lot of value, for example in advancing the underwriting approach

Objective

- Build a model in the approval process to predict the collateral value of an application and identify segment-level Conversion Factor for more accurate $ loss rate prediction

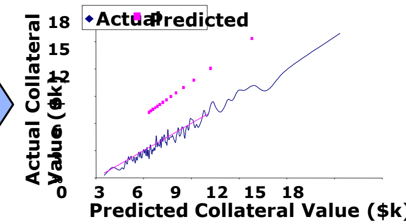
Approach



	<100	100-109	110-119	120-129	130+
P	0.51	0.49	0.54	0.60	0.58
S	0.55	0.53	0.56	0.61	0.61
B	0.64	0.61	0.62	0.67	0.65

Variable	Univariate	Bivariate	Mutlivariate
emplyr			
yrinhm	1	1	1
yrinbiz	1	1	
cst_typcd	1		
revcredn			
revcred	1	1	1
sbss			
revbrd	1		
PRODUCT			
pgdeal	1		

Predicted vs. Actual Collateral Value

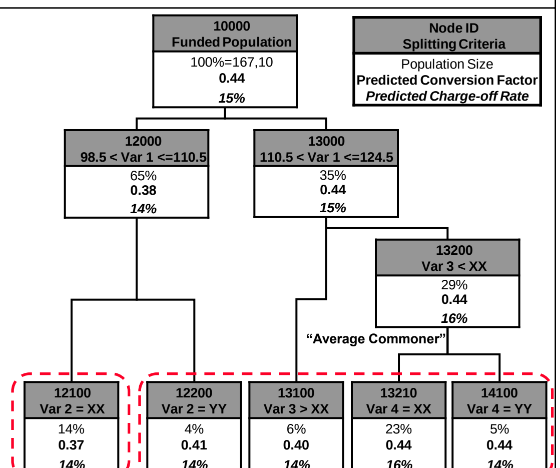


Illustrative

Impact

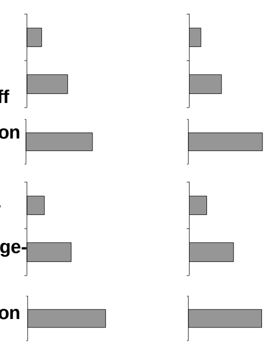
- Generated a significant in-years impact (>$10mm) from using different conversion factors for different segments of the population via
  - Better decisioning and credit risk ($6-7mm)
  - Improved market place product pricing ($3-4mm)

Conversion Factor Lookup Table



Major Segments by Conversion Factor

Segment	Conversion Factor	Nodes		Predicted Values	Actual Values
Nouveau-Riche	Low	11000 12100	$ charge-off Rate Unit charge-off Rate Conversion Factor		
Average Commoner	Moderate	12200 13100 13210 14100	$ charge-off Rate Unit charge-off Rate Conversion Factor		



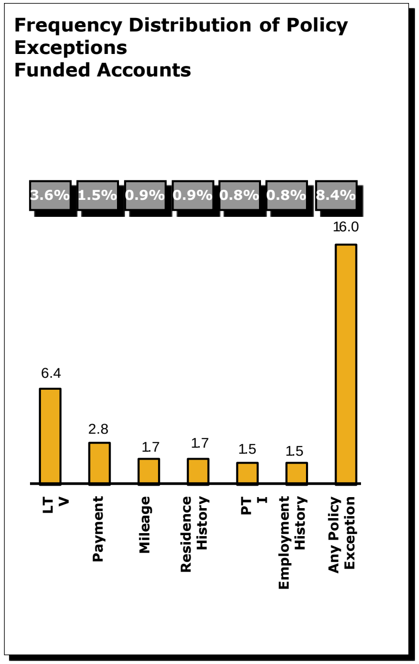
Case 2: Back-End Optimization and Exception Handling

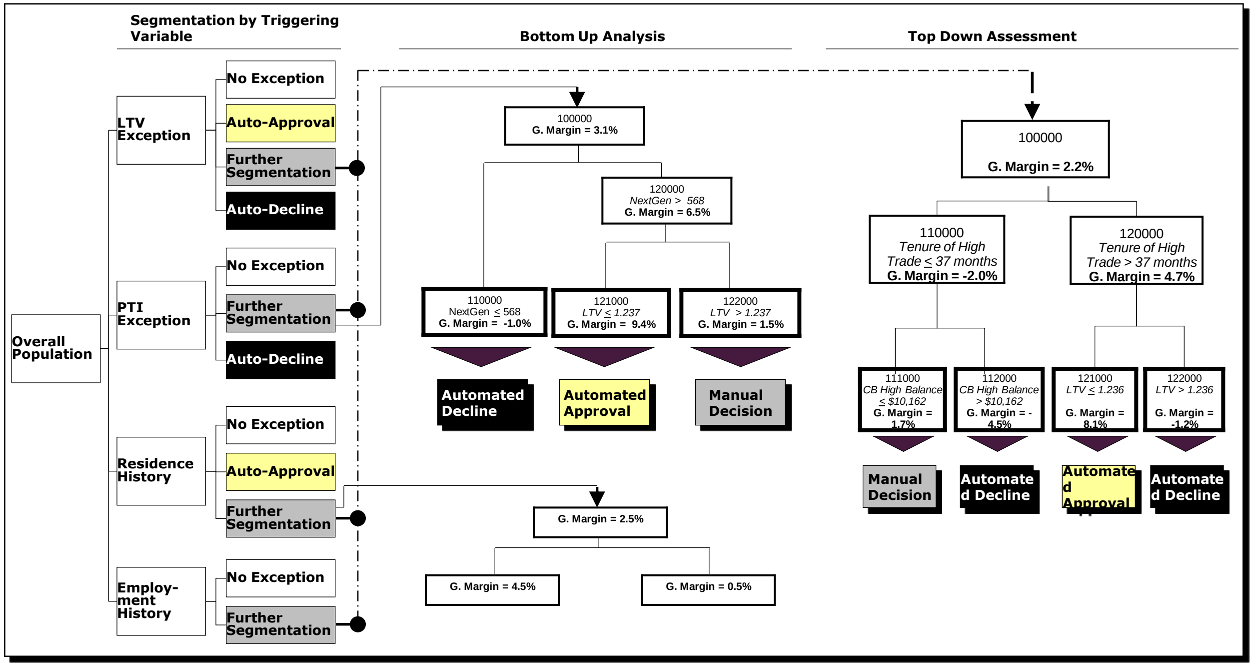
Effectively leveraging all information available at underwriting helps us further enhance our decisioning at the back-end of underwriting as well

There are significant changes in the deal information which results in sub-optimal exceptions

By leveraging:
- Time series in information change
- Developing a forward-looking value metric and
- Segmenting the population based on value, risk and information change

we can significantly limit losses on the portfolio



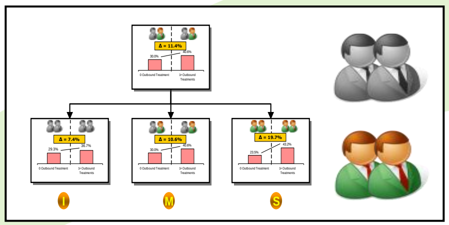


Case 3: Enhancing Recoveries and Treatment Optimization

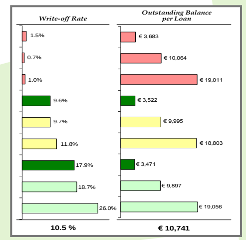
Recovery rates were significantly improved by combining traditional approaches with Sensitivity-based techniques

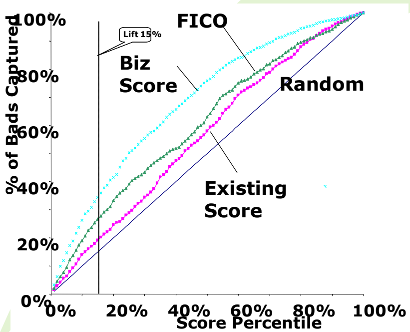
Combining traditional approaches, such as Payback Likelihood and Customer values models…

…With sensitivity-based segmentation focusing on response to treatments (letters, IVR, dialer, others)…



…we can construct a comprehensive optimization engine which enables us to maximize the amount recovered





In addition to predictive models and sensitivity segmentations, we leveraged additional customer, vehicle and contract attributes to optimize the treatments

Case 3: Enhancing Recoveries and Treatment Optimization

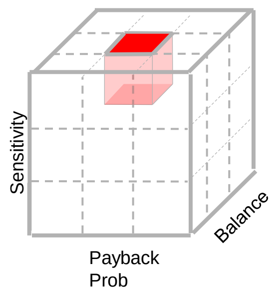
Using different dimensions, such as Payback Likelihood, Sensitivity and Balance, among others we segmented the population and optimized the treatment strategies

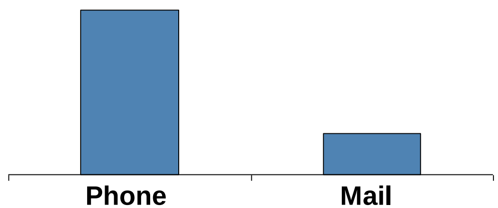
Illustrative

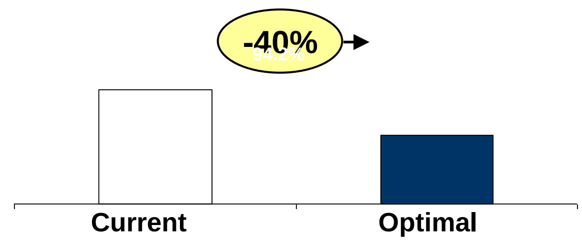
Different segments have different treatments sensitivity

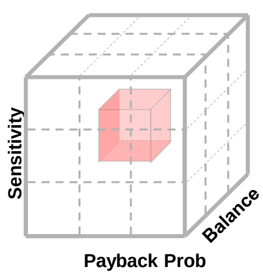
Similar treatment intensity across different levers…

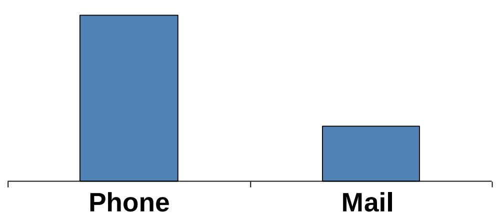
…results in almost double impact for sensitive segments

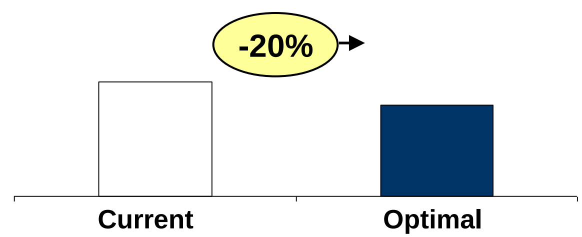






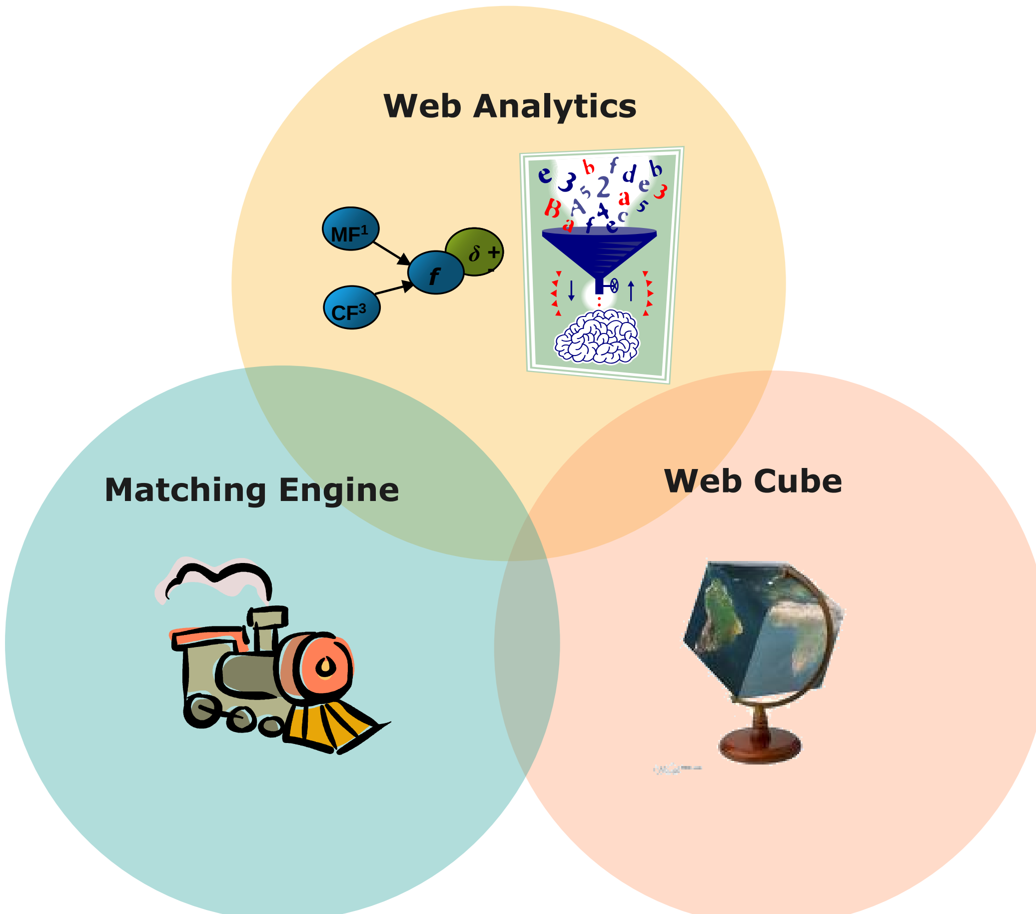






Case 4: Driving Growth through Web Analytics

Emerging techniques leverage the wealth of new data and new analytical approaches to unlock customer value, particularly at acquisitions



Case 4: Driving Growth through Web Analytics

Collaborative Filtering (CF) is one broad family of recommender system that leverages past user behavior to infer potential user interest

Recommender Systems

Recommender Systems

- Recommender systems are programs and algorithms that measure the interest in given items or products to provide personalized recommendations for items that will suit the user's taste
- High quality personalized recommendations deepen and add another dimension to the user experience to drive economic impact

Content Based Approach

- Matching user profile to product features
- Hard to gather external information

Collaborative Filtering (CF)

- CF analyzes relationships between users and interdependencies among products, in order to identify new user-item associations.
- CF relies only on past user behavior without requiring the creation of explicit profiles.

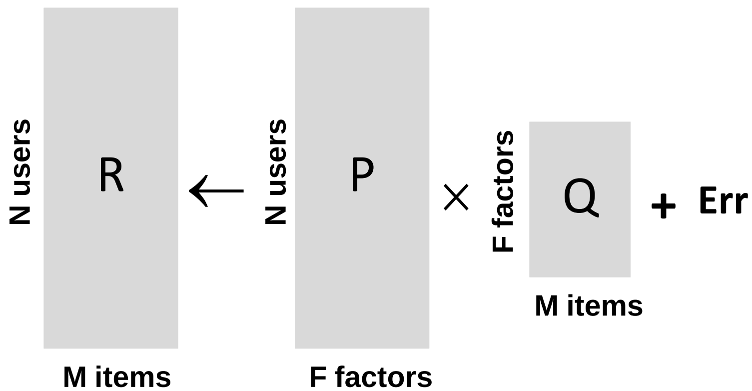
Emerging

Case 4: Driving Growth through Web Analytics

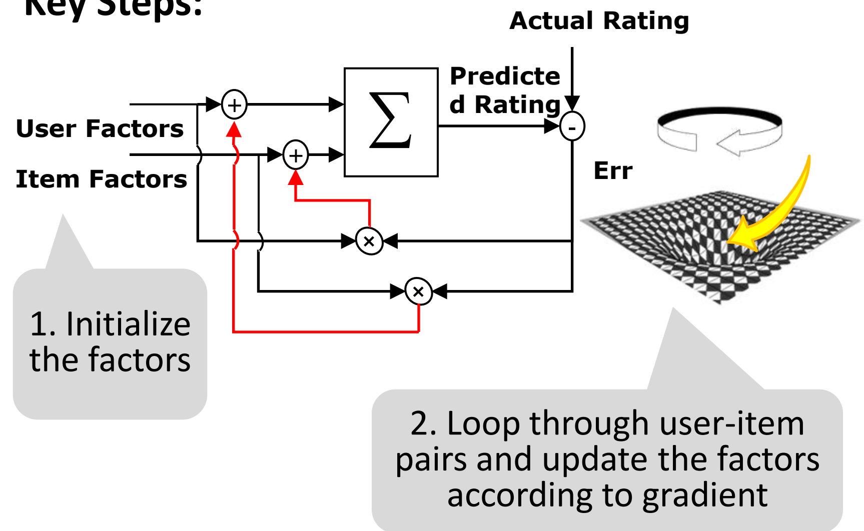
Factorization-based Estimation decompose user*item matrix into user*factor and factor *item matrixes, which can be used for prediction

Collaborative Filtering – Factorization Based

Algorithm Diagram:



Key Steps:



Detail Algorithms:

- Online SVD
- Batch SVD
- Regularized SVD (RSVD)
  - Gaussian prior
- Neighborhood-aware SVD
  - MSE
  - Support-based

Comment:

A “Regional” approach: uses a limited set of factors to characterize all users and items

Case 4: Driving Growth through Web Analytics

Neighborhood-based Estimation (“k-nearest neighbors"): a user-item preference rating is interpolated from ratings of similar items and/or users.

Collaborative Filtering – Neighborhood Based

Prediction Rule:

$$r_{ui} \leftarrow \sum_{j \in N(i;u)} w_{ij} r_{uj}$$

unknown rating by user u on item i

known rating by user u on item j

for all items rated by u in i‘s Kth nearest neighborhood

interpolation weights

Key Steps:

1. Rating Normalization
   a. Offset user/item related averages
   b. Treat factorization model as normalization
2. Neighborhood Selection
   a. Similarity metric (correlation, distance)
   b. Similarity calculation
3. Determination of interpolation weights
   a. Direct interpolation
   b. Globally optimized

Detail Algorithms:

- Item-oriented KNN
- User-oriented KNN
- Naive pair-wise KNN
- MSE KNN
- Support-based KNN
- Post-processing residual of factorization and RBM

Comment:

A “Local” approach: only looks around other items rated by the same user

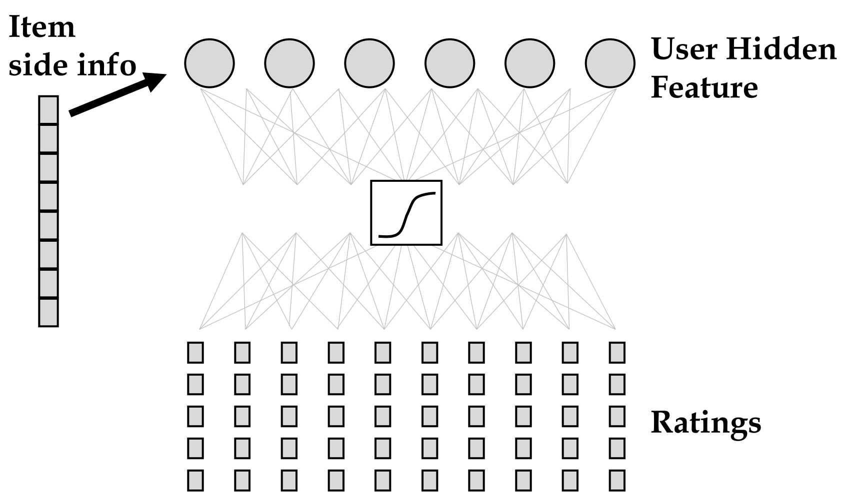
Case 4: Driving Growth through Web Analytics

Emerging

Neural Network family is an altered version of factorization-based estimation, which correct over-fitting by restricting number of parameters and introducing discontinuous energy jump

Neural Network

Algorithm Diagram:



Detail Algorithms:

- Restricted Boltzmann Machines (RBM)
  - Multinomial visible units
  - Gaussian visible units
- Asymmetric factor models (AFM)
  - Weighted score
  - Identical input/output matrix
  - Weighting with residuals

Key Steps:

1. Only parameterize items
2. Loop through users
3. Transform ratings to weights (AFM) or totally eliminating the order of the ratings (RBM)
4. Initialize the factors with fixed small value (AFM) or vector with Gaussian distribution
5. Use gradient update (AFM) or discreet energy jump (RBM) to train the item factors

Comment:

A “generalization” and “alternative” of factorization-based approach

Key Challenges and Opportunities

Domain	Key Challenges
Traditional	▪ Driving decision-making consistency across a diverse set of platforms and processes ▪Using the right tools for the right problem ▪Avoiding overfitting
Sensitivity -Based	▪Lack of robust "off-the-shelf" tools and techniques ▪Ability to incorporate results in existing decisioning processes
Emerging	▪Extracting predictive power from extremely "thin" data ▪Increasing transparency of modeling techniques ▪Ability to leverage and visualize large volumes of dynamic data