The Remarkable Transition in Consumer Dynamics and Marketing Analytics – The Last 50 Years and the Future

Professor Glen Urban December 7,2016

1966 - 2016

CONSUMER DYNAMICS

- 1966-76
 - Advertising/Promotion
 - Abundance/Buying power
 - New Products
- 1977-86
 - Brand loyalty
 - UPC Data
 - Brand Power

MARKETING ANALYTICS

- 1966-76
 - Computers in Marketing
 - Marketing Science
 - Brandaid/Assessor/Switching
- 1977-86
 - LOGIT/Conjoint models/ perceptual mapping
 - Decision Support Systems/on line models
 - Econometrics

50 YEAR TRANSITON

CONSUMER DYNAMICS

- 1987-96
 - Internet
 - Consumer Power
 - Trust
- 1997-2006
 - Google
 - Amazon/eBay
 - Big Data

MARKETING ANALYTICS

- 1987-96
 - CRM/Trust Determinants
 - Information Acceleration / Game Theory
 - Dash Boards
- 1997-2006
 - Analytics Tool Kit
 - Targeting Ads
 - Behavioral Economics

LAST DECADE

CONSUMER DYNAMICS

- 2007-2016
 - Social Media
 - Youtube
 - Mobile

MARKETING ANALYTICS

- 2007-2016
 - Market/Behavioral Experimentation
 - Hierarchical Bayesian Models
 - State of the Art -- Morphing
 Ads/Deep Learning

STATE OF THE ART - MORPHING

- Next step after targeting
- Who to target to How to communicate to them individually
- Cognitive style and communication in ads and web site
- Cognitive Styles: Analytical/Holistic, Impulsive/ Deliberative, Visual/Verbal, Rational/Intuitive

AD MORPHING



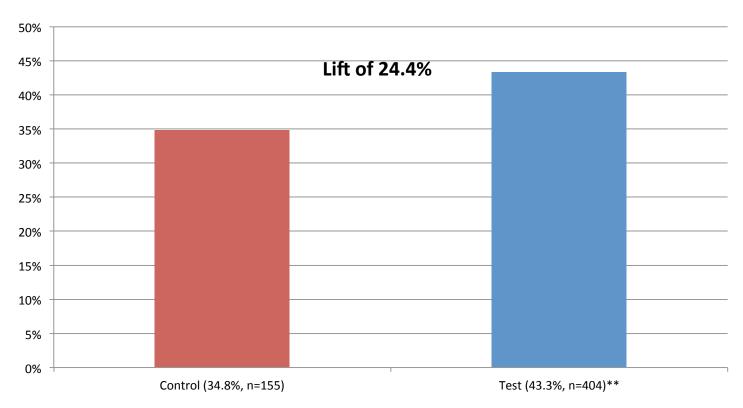




- Estimate cognitive style
- Match ads to cognitive style by continuous experimentation/Machine Learning
- Individual assignment of Messaging
- Matching cognitive style builds trust and consideration and sales

CHEVROLET CONSIDERATION

Measures consideration of Chevrolet by a participant for his or her next vehicle.



Project – AT&T Cnet Market Experiment

Data Collection Consumer Profiling

Targeting by Cognitive Style

Analysis of Results

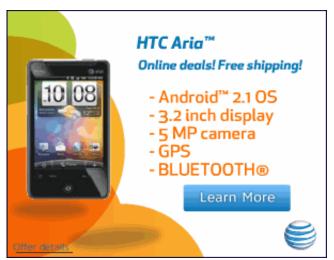
- Track clickstreams on CNET.com
- Survey small segment to determine cognitive style
- Using MIT decisioning engine, determine cognitive style of cookies using clickstreams
- Remessage cookies on CBS ad network
- Morph AT&T banner messaging to cognitive style
- Measure lift in clickthrough rate behavior for morphed vs. unmorphed AT&T ads







Holistic - Deliberative



Analytic - Deliberative



Holistic - Impulsive



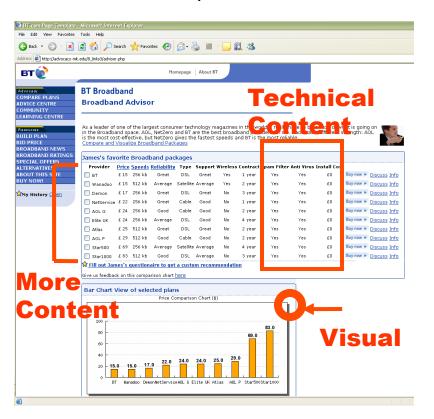
Analytic - Impulsive

CNET MARKET RESULTS

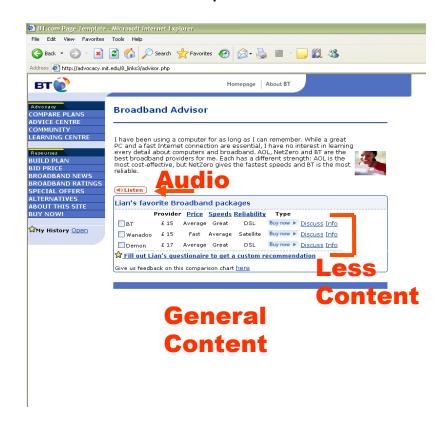
- 27,000 users and
- 63,000 sessions
- CTR .25% TEST VS .13% CONTROL
- Lift of 92% in click rate
- Morphing works

WEBSITE MORPHING

Morph 1



Morph 8





ウェルカムページ ホーム

データ アドバイザー 早わかり 基礎知識 レビュー掲示板 カスタマイズページ

モーフィングを止める

Fixed Morphs 000000 111111



データ

詳しいデータを分析する 返済計画を計算する

- カードローン一覧表
- 返済計画ツール



基礎知識

基礎からじっくり詳しく 学ぶカードローンの知識



アドバイザー

おすすめカードローン を探して全体像をつか む



レビュー掲示板 他の人の意見を見る



早わかり

時間のない方へ すぐに分かるカードロ ーン



カスタマイズ ページ

あなたのニーズに合わ せてサイトをカスタマ イズ



RESULTS

- 1,000+ person panel studies A/B design
- Increase consideration 25%
- Probability of purchase 20% increase

FUTURE OF MORPHING

- Easy to use
- Creative links not just format but strategic
- Cross media morphing
- Opt In or protect privacy
- Next step in building trust

STATE OF THE ART – DEEP LEARNING

- Hot new technique
- Big Data and Al
- Success in Voice, hand writing, visual recognition
- Can be used in Marketing Analytics?
 - Targeting/Morphing
 - New Products
 - Decision Support

Deepmind: The Mystique of Deep Learning

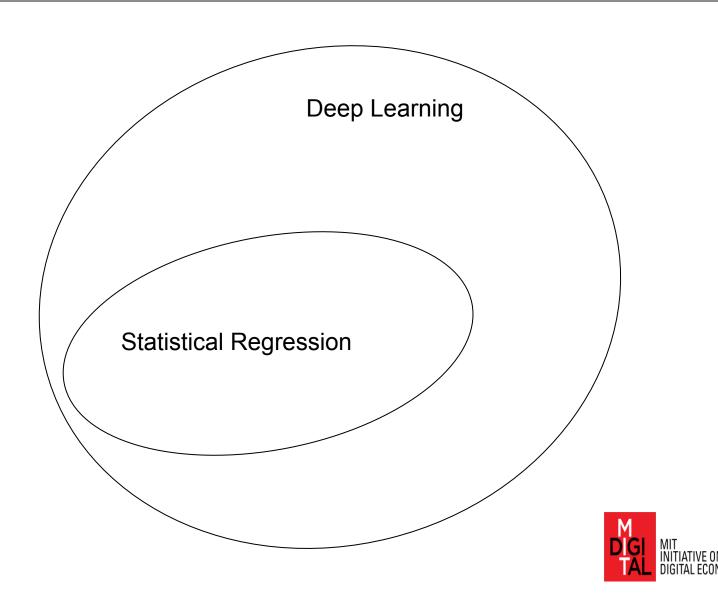


Initiative on the Digital Economy -- IDE

- 4 Program Areas
 - Productivity and Employment
 - Data and Information Privacy
 - ❖ New Business Models
 - Social Dynamics and Market Experimentation Section
- Foundation, Corporation, and Individual support
- Deep Learning in Marketing supported by Suruga Bank

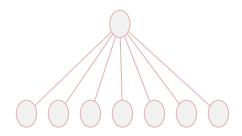


Deep Learning in Marketing



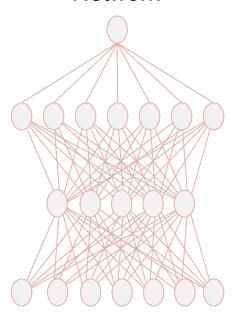
Functional Form

Linear Regression



Maximum Likelihood Interpretable Linear

Neural Network



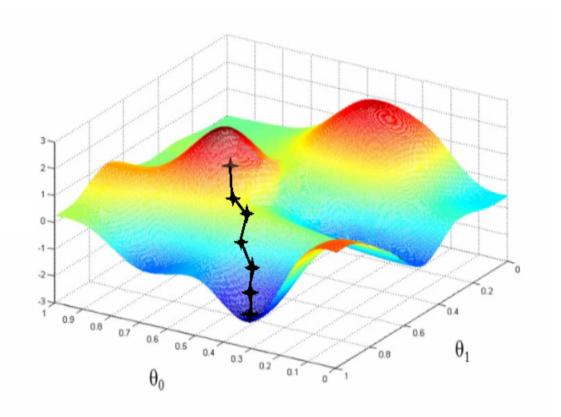
Search method required, many suboptimal solutions.

Not easily interpretable Nonlinear



Stochastic Gradient Descent

Minimize error using gradient descent methods.





Two Communities with Different Approaches

Classical Statistics

Deep Learning

- •High emphasis on error term assumption & statistical properties
- •Emphasis on prediction "It works"

- •Simplicity & interpretability Theory
- Complex neural net

Use selected data

Use Big data

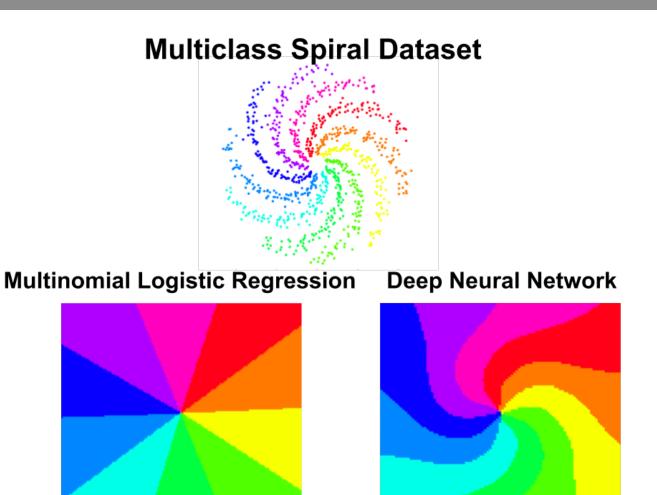
Statistical Heritage

Artificial Intelligence

- Custom collection of data
- Lower cost Big Data



Deep Neural Networks are Non-linear



92% Accuracy

34% Accuracy



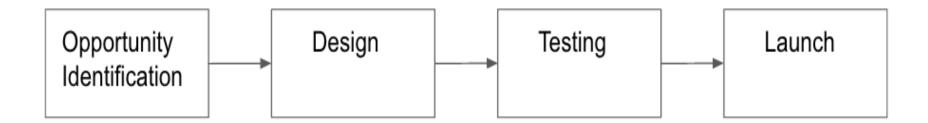
Can We Apply Deep Learning to New Products

If we have click data from relevant product selection site can we find new product opportunities?



Deep Learning in Marketing

Finding Opportunities for New Products





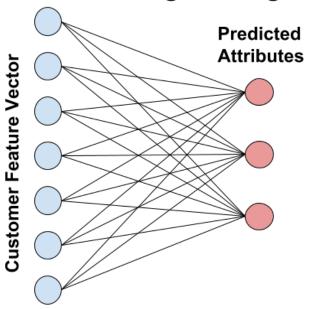
Approach

- Credit card advisor selection site
- Synthetic click data from "true" customer plus error
- Can we predict card selection (attributes) ?
- Empirical Data for Credit Cards early results
- What are the implications for new credit cards?

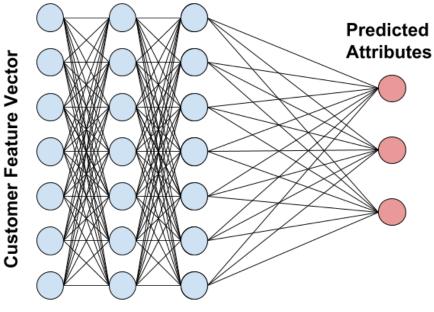


Credit Card Functional Form

Multinomial Logistic Regression



Deep Neural Network



Representation Layers Classification Layer



Neural Net Model

Realized product interest



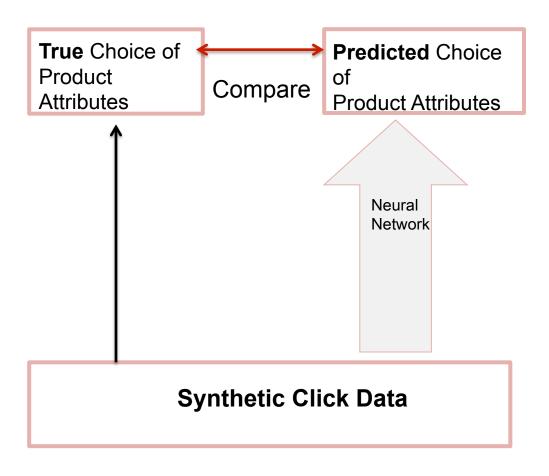
Neural Network

Customer click data



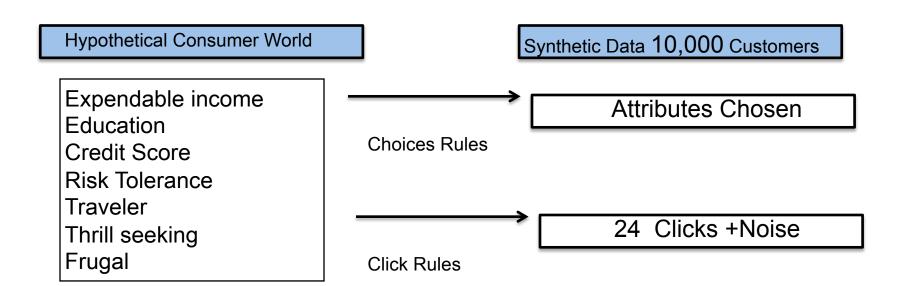


Methodology





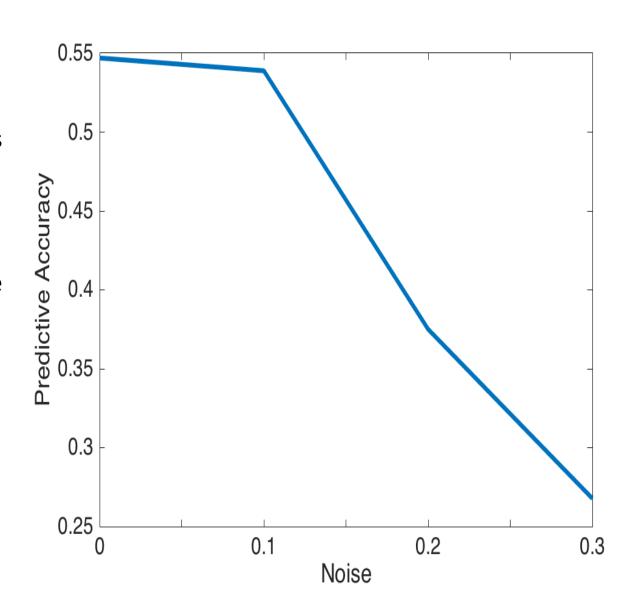
Synthetic Data Model





Comparison of True and Predicted

- 10% Noise
- 54% All Four
 Attributes No errors
- Good Recovery by Neural Net
- Depends on our noise generation - if 20% noise then only 38% correct



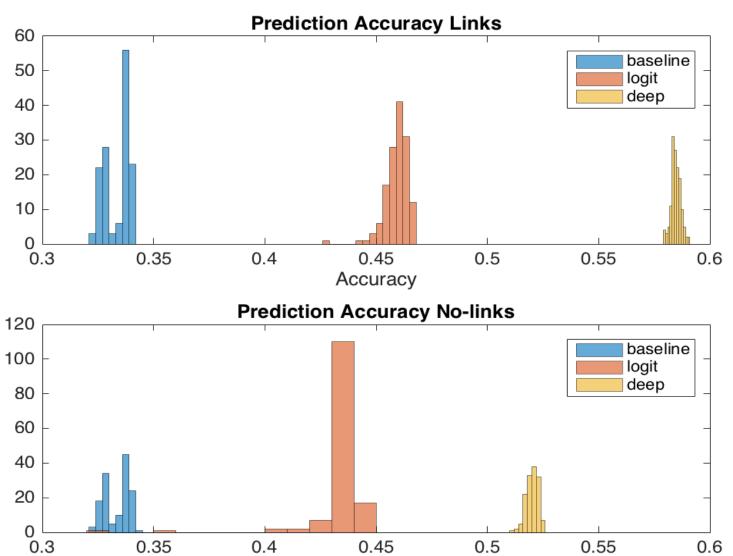
EMPIRICAL DATA – CREDIT CARDS

- Comscore Panel
 - -55,000
 - All clicks
- 15 Bank Credit Card Sites --BOA, CITI, DISCOVER, ETC
 - Average 28 clicks per person
 - 30% visit more than one site
- Variables
 - Annual Percentage Rate (e.g. intro, duration, ongoing)
 - Reward (e.g. amount, miles/cash)
 - Demographics (e.g.age, income, zip, machine id)
 - URLs (across banks)

EMPIRICAL RESULTS

- Deep Learning model
 - Two levels
 - 50% data for fit, 25% validation, 25% test
 - Bootstrap for significance
- Accuracy
 - 52% correct in test data significant at .1%
 - Significantly better than simple multinomial LOGIT
 - Links significant contributors to accuracy

Empirical Results



Accuracy



Add a new product

Rewards Program	Rewards Rate	Interest Rate
Cashback	1%	24.99%
Reward Points	2%	22.99%
Miles	1%	16.99%
Miles	1.5%	13.9%

Market Share	Profit (\$M)
53.6%	198
17.1%	63
9.4%	35
19.9%	73



Add a new product

Rewards Program	Rewards Rate	Interest Rate
Cashback	1.5%	14.99%
Cashback	1%	24.99%
Cashback	1%	29.99%
Cashback	1.5%	12.9%

Market Share	Profit (\$M)
14.4%	47
31.2%	103
14.8%	49
39.6%	130

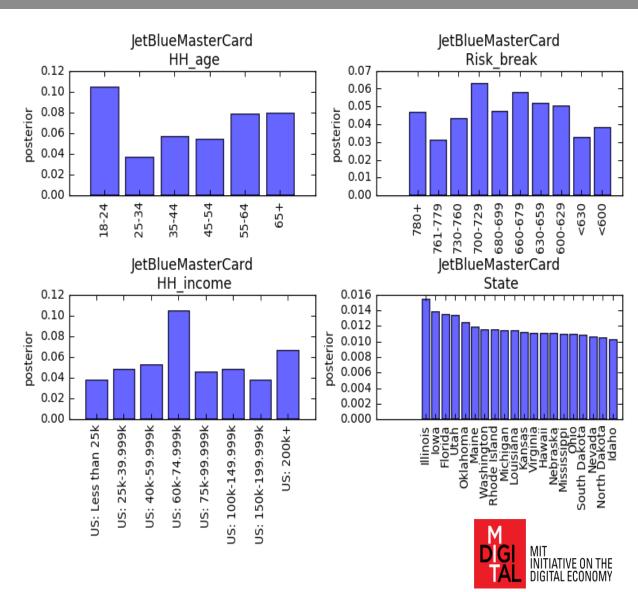


What target market do we attract

Rewards Rewards Raterest Rate

Travel 1% 12.24%





Optimal Card for a Given Customer

US: Less than 25k Delaware 45-54 <630 ProductDetail

Disney Reward Premium Visa

Delta Sky Miles Gold

Venture One Rewards Visa

US: 200k+ California 45-54 780+ ProductDetail

Classic Platinum MasterCard

Barclaycard Rewards Mastercard

Marriot Rewards Premier Business Card



Deep Learning Research Future Work

Add new click data for advisor/comparison/choice websites (Creditcarma, Nerdwallet, Lending tree)

Technical – Restricted Boltzmann Model Recurrent neural networks

Other Marketing Problems –
Consumer Brand Loyalty
Media Allocation
Advertising Response
Morphing

Does Deep Learning predict better than classical statistical methods -- conjoint?



Emerging Conclusions Deep Learning

Can recover synthetic data choice

Early empirical results are encouraging

Identify new product opportunities

Looking for IDE Partners – Financial / Consumer Durables



Next Ten Years?

CONSUMER DYNAMICS

- Saturation of markets
- Volatility preferences and economics
- New media virtual reality
- Technology/data change block chains/automated driving

Marketing Analytics

- Innovation Support New Product Needs
- More power in Computers/ networks/data
- New Models/Machine Learning Algorithms
- Managerial Models

SUMMARY

- Exciting 50 years
- More Opportunities to Come Best Time Ever
 To Be in Marketing
- Prepare for the unexpected
- This conference is look ahead at future of consumer dynamics and analytics