Psychological Advertising: Exploring User Psychology for Click Prediction in Sponsored Search

Taifeng Wang¹, Jiang Bian¹, Shusen Liu², Yuyu Zhang³, Tie-Yan Liu¹

¹Microsoft Research Asia
²South China University of Technology
³Chinese Academy of Science
Sponsored Search

 Bing Sponsored Search Results

man shirt

271,000,000 RESULTS  Any time

Ralph Lauren® Online | Ralphlauren.com ©
www.RalphLauren.com
Shop the Official Site for Ralph Lauren Apparel, Accessories & More.

LL Bean Man's Shirt - 10% Off Your Full Order Today ©
www.LLBBean.com
Free Shipping & Free $10 Gift Card.

Buy Men's Shirts - Buy Men's Shirts Online ©
JiffyShirts.com/Men's-Shirts
Up to 55% off Retail. In Stock. Ships Free!

Lands' End® Men's Shirts - Polo Shirts, Dress Shirts & More ©
www.LandsEnd.com/Mens
Shop Men's Shirts at Lands' End.

Shop for man shirt
bing.com/shopping
Department: Men | Women | Girls | Boys | Toddler boys
Special size: Plus size, Big & tall, Juniors, Petite, Maternity

Men's Gildan Sweatshirt $7.15
Men's 100% Linen Shirt $75.00
Men's Classic Fit Sweatshirt $45.00
Golf Clubs Camp Havaianas $44.95
Men's Flannel Shirts $15.99

men shirt | eBay | Electronics, Cars, Fashion, Collectibles ©
www.ebay.com/sch/mens-shirt/i.html?_nkw=mens+shirt
Find great deals on eBay for mens shirt and mens shirts large. Shop with confidence.

The Man Shirt ©
www.CafePress.com
Unique The Man T-Shirts for Everyone. 1000s of Designs!

Best Dress Shirts ©
www.EddieBauer.com/DressShirts
Spring Sale - Save up to 50%. Free Shipping On Orders Over $59.

Iron Man T-Shirts ©
www.DisneyStore.com/Iron_Man
Show Your Superhero Style. Shop Iron Man Tees at Disney Store!

75% Off Men's Clothing ©
HauteLook.com
50-75% Off Men's Designer Clothing. Join Free and Shop Now!
hautelook.com is rated ★★★★★ on Bizrate (2489 reviews)

Hansens Clothing Inc ©
hansensclothing.com
Free Men's Clothing Online. Free Shipping & Free Mattresses

Merona Shirts $20 ©
http://www.Target.com
Find Merona Shirts For $20 At Your Local Target!
See your message here

RELATED SEARCHES
Sponsored Search

9/2/2013
Talk at PKU
Click Prediction in Sponsored Search
Click Prediction in Sponsored Search

- Search Query
  - Ad Selection By Match Type
    - Exact
    - Broad
  - Ad Inventory
    - KWs
    - Ad Copy
Click Prediction in Sponsored Search

- Search Query
  - Ad Selection By Match Type
    - Exact
    - Broad
  - Ad Inventory
    - KWs
    - Ad Copy

- Scoring
  - Click probability ($p_{\text{Click}}$)

Click prediction
Click Prediction in Sponsored Search

- **Search Query**
  - Ad Selection By Match Type
    - Exact
    - Broad
  - Ad Inventory
    - KWs
    - Ad Copy

- **Scoring**
  - Click probability (pClick)

- **Filtration**
  - Relevance/ pClick threshold
  - Filtration: remove an ad if its $\text{pClick} < \text{Threshold}$

- **Ranking**
  - Ranking by revenue
  - Ranking: Rank Score($RS$) = $\text{pClick} \times \text{Bid}$

- **Allocation**
  - Mainline
  - Sidebar
  - Allocation: $RS > \text{Reserve Threshold}$

- **Pricing**
  - Pricing with GSP
  - Pricing: $\text{CPC}_i = \frac{RS_{i-1}}{\text{pClick}_i}$
State-of-The-Art Click Prediction Modeling

Click Probability

Machine Learning Model
State-of-The-Art Click Prediction Modeling

- Relevance features
  - *What* relevant content users seek to click

Machine Learning Model

Click Probability

Relevance features *(What)*
State-of-The-Art Click Prediction Modeling

Machine Learning Model

Click Probability

- Relevance features
  - *What* relevant content users seek to click

- Historical click features
  - *How* users click
State-of-The-Art Click Prediction Modeling

- Relevance features
  - *What* relevant content users seek to click

- Historical click features
  - *How* users click

What can help us answer *why* users click?
Relevance Is Not Enough
Relevance Is Not Enough
Relevance Is Not Enough
Relevance Is Not Enough
Relevance Is Not Enough

If directly using relevance score to predict clicks, the accuracy will be very low: AUC of BM25 is just 0.55 (very close to random guess!)

(Dataset: production pClick training data set with 15M ad impression, ~2M query event)
Relevance Is Not Enough

If directly using relevance score to predict clicks, the accuracy will be very low: AUC of BM25 is just 0.55 (very close to random guess!)

(Dataset: production pClick training data set with 15M ad impression, ~2M query event)

Explanations:

• Many ads, especially for popular queries, yield similar relevance and cannot be well distinguished by their relevance scores.

• Users come to search engine for info but not for ads (ads are pushed to them). Therefore users do not necessarily click on relevant ads because ads are not what they actively look for at all.
Other Click ⟷ 1 Click

Hotel in Las Vegas - Save up to 50% on your Hotel
www.ORBITZ.com/Hotel_Sale
Limited Time Only - Don't Miss Out!
Check-In Tonight · Check-In This Weekend · Orbitz Hotel Sale

CTR range: percentage of users of different CTR Range

- [0%, 15%): 20.02%
- [15%, 100%): 79.98%

---

Hotel In Las Vegas - Las Vegas All Suite Luxury Resort
Palazzo.com/VegasIsThePalazzo
Arrange An Extravagant Getaway Now!

CTR range: percentage of users of different CTR Range

- [0%, 15%): 24.73%
- [15%, 100%): 73.26%
Given the same query-ad pair (with the same historical click counts), the variance of different users’ CTRs can be very large. Historical click counts, which reflect the mean of these CTRs, will lead to a significant prediction error, which corresponds to the variance of these CTRs.
Other Click ↦ I Click

Given the same query-ad pair (with the same historical click counts), the variance of different users’ CTRs can be very large. Historical click counts, which reflect the mean of these CTRs, will lead to a significant prediction error, which corresponds to the variance of these CTRs.

Explanations

- Users are not identical: their click behaviors (preferences on the same ad) are highly diverse, personal, and time-varying.
- One person may not necessarily click on an ad even if many other people click on it.
Then, What Else Should We Use?

• To answer *why* users click
  • Characterize the motivation of clicks beyond relevance
  • Distinguish diverse click behaviors of different users

• Our proposal
  • Leverage the study on user behaviors in the literature of behavior economics and advertising, and attribute the motivation of user clicks to the satisfaction of their psychological desire.

*Psychological factors is one of the central design principles in the advertising industry*
Roadmap

• Motivations
• Data Analysis on User Psychological Desires
• Discovering User Psychological Desire from Ads
• Click Prediction Modeling
• Experimental Evaluations
Psychological Desire in Consumer Decision Making Process

- Problem Recognition
- Information Search
- Judgement and Decision Making
- Post-purchase Evaluation

W. D. Hoyer and D. J. Maclnnis. *Consumer Behavior.*
Psychological Desire in Consumer Decision Making Process

W. D. Hoyer and D. J. Maclnnis. *Consumer Behavior.*

User Psychological Desires

Problem Recognition

Information Search

Judgement and Decision Making

Post-purchase Evaluation

Thought-based Factors

Contextual Effects

Feeling-based Factors
Psychological Desire in Consumer Decision Making Process

W. D. Hoyer and D. J. Maclnnis. *Consumer Behavior.*

**User Psychological Desires**

<table>
<thead>
<tr>
<th>Effects</th>
<th>User Desires</th>
<th>Examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thought-based (quantifiable)</td>
<td>Petty advantage</td>
<td><em>big discount, good deal, coupon</em></td>
</tr>
<tr>
<td></td>
<td>Quantity/quality advantage</td>
<td><em>Popular brand, large selection space</em></td>
</tr>
<tr>
<td></td>
<td>Extra convenience</td>
<td><em>Quick delivering, flexible payment method</em></td>
</tr>
<tr>
<td>Feeling-based (subjective)</td>
<td>Trustworthy</td>
<td><em>Official seller, service with guarantee</em></td>
</tr>
<tr>
<td></td>
<td>Brand loyalty</td>
<td><em>Ebay, Amazon</em></td>
</tr>
<tr>
<td></td>
<td>Luxury seeking</td>
<td><em>First class brand</em></td>
</tr>
</tbody>
</table>

**Problem Recognition**

**Information Search**

**Judgement and Decision Making**

**Post-purchase Evaluation**

9/2/2013 KDD'13 - Psychological Advertising 9
Psychological Desire in Ads Copy

Query: **nike**

- **Free Nike Coupons**
  Download And Print Nike Coupons (100% Free)

- **Nike - Sale Prices**
  Latest Fashions and Styles on Sale. Buy Nike Fast!

- **AKADEMA Baseball Outlet**
  PRO, ROOKIE, FASTPITCH, APPAREL BATS, MITT & GLOVES
  $7.99 - 199.99

Cheap/free, try to get something with less cost.

Query: **perfume**

- **Perfume.com official site**
  10,000+ brand name perfumes and colognes - up to 80% off retail!

- **Luxury English Perfume**
  Shop online for luxury perfumes for men, women & the home!

- **Versace Perfume**
  The Scent of You. Discover Versace Perfume!

Authoritative and Trustable

Query: **HP Drivers Download**

- **HP Drivers Download**
  (Recommended) Download HP Drivers. Download HP Drivers in Seconds.

- **HP Drivers Download**
  Free Download: HP Drivers Update. Download & Install HP Drivers Now

- **HP Drivers Downloads**
  (Recommended) HP Printer Drivers. HP Drivers Download Center.

Quick effect, action triggering
Psychological Desire in Ads Copy

Ads with some explicit patterns can rise people’s certain desire to interact. Let’s take a deeper study.

Cheap/free, try to get something with less cost.
Effects of User Psychological Desire

- CTR difference between the ads matched with user desire pattern and overall ads

<table>
<thead>
<tr>
<th>Desire pattern</th>
<th>Coverage of ads</th>
<th>CTR change</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thought-based</td>
<td></td>
<td></td>
</tr>
<tr>
<td>“coupon”</td>
<td>2.2%</td>
<td>+47.5%</td>
</tr>
<tr>
<td>“x% off”</td>
<td>4.1%</td>
<td>+19.7%</td>
</tr>
<tr>
<td>Feeling-based</td>
<td></td>
<td></td>
</tr>
<tr>
<td>“official”</td>
<td>2.6%</td>
<td>+25.0%</td>
</tr>
<tr>
<td>“return guarantee”</td>
<td>1.9%</td>
<td>+31.4%</td>
</tr>
</tbody>
</table>

9/2/2013
KDD'13 - Psychological Advertising
Roadmap

• Motivations
• Data Analysis on User Psychological Desires
• Discovering User Psychological Desire from Ads
• Click Prediction Modeling
• Experimental Evaluations
Discovering User Psychological Desire

• Principles to extract content reflecting user desires from ad texts:
  • Ad content = relevance + desire
  • Reflecting user desires in terms of CTR difference
  • Enough volume coverage in ad traffic
  • Generalized into *user desire pattern* – similar content reflecting the specific same desire
  • Content from experienced advertisers are more important
Discovering User Psychological Desire

- Principles to extract content reflecting user desires from ad texts:
  - Ad content = relevance + desire
  - Reflecting user desires in terms of CTR difference
  - Enough volume coverage in ad traffic
  - Generalized into user desire pattern – similar content reflecting the specific same desire
  - Content from experienced advertisers are more important

**Step-1:**
Cleaning up content for relevance

- Remove query and bid keyword
- Tokenize digits and locations

Ads corpus + logs
Discovering User Psychological Desire

Principles to extract content reflecting user desires from ad texts:

- Ad content = relevance + desire
- Reflecting user desires in terms of CTR difference
- Enough volume coverage in ad traffic
- Generalized into user desire pattern – similar content reflecting the specific same desire
- Content from experienced advertisers are more important

Step 1:
Cleaning up content for relevance

- Remove query and bid keyword
- Tokenize digits and locations

Step 2:
Finding n-grams with high frequency and significant CTR change

Ads corpus + logs

n-grams
Discovering User Psychological Desire

- Principles to extract content reflecting user desires from ad texts:
  - Ad content = relevance + desire
  - Reflecting user desires in terms of CTR difference
  - Enough volume coverage in ad traffic
  - Generalized into user desire pattern – similar content reflecting the specific same desire
  - Content from experienced advertisers are more important

**Step-1:** Cleaning up content for relevance
- Remove query and bid keyword
- Tokenize digits and locations

**Step-2:** Finding n-grams with high frequency and significant CTR change

**Step-3:** Pattern generalization via clustering
- N-grams from experienced advertisers are more important
- The mature status of an advertiser - the number of clicks targeting at any of his/her ads in one month.
- The weight of an n-gram - the maximum mature status among advertisers who ever used the n-gram in their ads.
Discovering User Psychological Desire

- Principles to extract content reflecting user desires from ad texts:
  - Ad content = relevance + desire
  - Reflecting user desires in terms of CTR difference
  - Enough volume coverage in ad traffic
  - Generalized into user desire pattern – similar content reflecting the specific same desire
  - Content from experienced advertisers are more important

**Step-1:** Cleaning up content for relevance
- Remove query and bid keyword
- Tokenize digits and locations

**Step-2:** Finding n-grams with high frequency and significant CTR change

**Step-3:** Pattern generalization via clustering
- N-grams from experienced advertisers are more important
- The mature status of an advertiser - the number of clicks targeting at any of his/her ads in one month.
- The weight of an n-gram - the maximum mature status among advertisers who ever used the n-gram in their ads.

Pattern database
- Hierarchy of pattern clusters
  - Hierarchical clustering for pattern aggregation in the same category
  - Maslow psychological hierarchy
Hierarchy of User Psychological Desire

Maslow's psychological hierarchy

- **Self-actualization**: Morality, creativity, spontaneity, problem solving, acceptance of facts
- **Esteem**: Self-esteem, confidence, achievement, respect of others, respect by others
- **Beloved/belonging**: Friendship, family, sexual intimacy
- **Safety**: Security of body, employment, resources, morality, family, health, properties
- **Physiological**: Breathing, food, water, sex, sleep, excretion
Hierarchy of User Psychological Desire

Maslow's psychological hierarchy

- **Self-actualization**: Morality, creativity, spontaneity, problem solving, acceptance of facts
- **Esteem**: Self-esteem, confidence, achievement, respect of others, respect by others
- **Beloved/belonging**: Friendship, family, sexual intimacy
- **Safety**: Security of body, employment, resources, morality, family, health, properties
- **Physiological**: Breathing, food, water, sex, sleep, excretion

Consumer psychological categories

- **Self-actualization**: Improve, learning, advance, career, become fashionable, guidance
- **Esteem**: Respected, first-class, just for you, VIP, high standard
- **Beloved/belonging**: Membership, social reviews, fast/free shipping, location convenience, hotline
- **Safety**: Quality of service, warrant, official, return policy, certificated
- **Physiological**: Direct and low-level requirement, e.g., petty advantages
People in different situations (belonging to different financial classes, with different ages, in different regions, in different social communities, facing different products) may belong to different psychological categories.
Active Psychological Needs Mining

Pattern database

Hierarchy of pattern clusters

Hierarchical clustering for pattern aggregation in the same category

- Maslow psychological hierarchy
Active Psychological Needs Mining

Pattern database

Hierarchy of pattern clusters

Hierarchical clustering for pattern aggregation in the same category

• Maslow psychological hierarchy

Psychological Needs

𝑝
def_k(C(p_k))

Patterns whose pseudo labels are certain enough

Most uncertain candidates

Uncertainty-based active learning

Label propagation

Labeled pattern candidates

Human Labeling (to predefined categories)

Refined candidate patterns

Pattern database

• Pattern similarity = term overlap
• Neighborhood graph construction based on similarity threshold
• Propagation based on personalized PageRank
• Compute pseudo label (mean) and uncertainty (variance)

2000+ patterns
Hierarchy of User Psychological Desire

<table>
<thead>
<tr>
<th>Self-actualization</th>
<th>Advance your career</th>
<th>Your dream</th>
<th>Achieve yours</th>
<th>Your ideal</th>
<th>Moments of yours</th>
</tr>
</thead>
<tbody>
<tr>
<td>Esteem</td>
<td>First Class</td>
<td>Top Quality</td>
<td>VIP</td>
<td>Ultimate Experience</td>
<td>Just for you</td>
</tr>
<tr>
<td>Belongingness</td>
<td>Find it Nearby</td>
<td>Call xxx-xxx-xxxx</td>
<td>Visa, Amex, Paypal Accepted</td>
<td>Hotels in Chicago</td>
<td>Same Day Shipping</td>
</tr>
<tr>
<td>Safety</td>
<td>365 Days Return</td>
<td>100% Guaranteed</td>
<td>Official site</td>
<td>20,000+ PCs &amp; Laptops</td>
<td>Customer Reviews</td>
</tr>
<tr>
<td>Physiological</td>
<td>Save money</td>
<td>Best price</td>
<td>x% off</td>
<td>Coupon</td>
<td>Free Shipping</td>
</tr>
</tbody>
</table>

-- *Succeed in reducing the sparsity of user desires for each individual ad*
Roadmap

• Motivations
• Data Analysis on User Psychological Desires
• Discovering User Psychological Desire from Ads
• Click Prediction Modeling
• Experimental Evaluations
Click Prediction Modeling

Problem:
Calculate the probability of click $p(c|q)$

$$w = \arg\max_w \left( \sum_{j=1}^{n} \log(p(c_i|q_i, a_i, u_i)) + \log(p(w)) \right)$$
Click Prediction Modeling

Problem:
Calculate the probability of click $p(c|q)$

- The maximum entropy model is well suited since its strength in combing diverse forms of features

\[
p(c|q, a, u) = \frac{1}{1 + \exp\left(\sum_{i=1}^{d} \omega_i f_i(q, a, u)\right)}
\]

\[
w = \arg\max_w \left(\sum_{j=1}^{n} \log(p(c_i|q_i, a_i, u_i)) + \log(p(w))\right)
\]

Feature set:
- Relevance features
- Historical click features

References:
- Cheng et al. WSDM 2010’
- Hillard et al. IRJ 2011’
- Richardson et al. WWW 2007’
Click Prediction Modeling

Problem:
Calculate the probability of click \( p(c|q) \)

- The maximum entropy model is well suited since its strength in combing diverse forms of features

\[
p(c|q, a, u) = \frac{1}{1 + \exp(\sum_{i=1}^{d} \omega_i i(q, a, u))}
\]

- The maximum entropy model learns the weight vector \( w \) by maximizing the likelihood of exponential models as:

\[
w = \arg\max_{w} \left( \sum_{j=1}^{n} \log(p(c_i|q_i, a_i, u_i)) + \log(p(w)) \right)
\]

Feature set:
- Relevance features
- Historical click features

References:
- Cheng et al. WSDM 2010’
- Hillard et al. IRJ 2011’
- Richardson et al. WWW 2007’
Integrating User Psychological Desires into Click Prediction
Integrating User Psychological Desires into Click Prediction

Pattern database

Modeling psychological desire as ad features

- Ad desire pattern features
- Ad desire category features

86% ads covered

ad: <0,0,...,0,1,0,0,...,1,0>
desire space

ad: <0,0,1,0,1>
desire category space
Integrating User Psychological Desires into Click Prediction

**Pattern database**

Modeling psychological desire as user features
- User desire pattern features
- User desire category features

Modeling psychological desire as ad features
- Ad desire pattern features
- Ad desire category features

86% ads covered
78% users covered

- Use ads clicked by a user to predict his preferences on pattern clusters
- Use patterns hit by ad copy to compute the needs addressed by the ad.

Historical click through log

user: \(<CTR_{p1}, CTR_{p2}, \ldots, CTR_{pn} >\)

desire space

user: \(<CTR_{c1}, CTR_{c2}, \ldots, CTR_{c5} >\)

desire category space
Integrating User Psychological Desires into Click Prediction

Pattern database

- Modeling psychological desire as ad features
  - Ad desire pattern features
  - Ad desire category features
  - 86% ads covered

- Modeling psychological desire as user features
  - User desire pattern features
  - User desire category features
  - 78% users covered

- Modeling desire matching features between users and ads
  - Desire pattern matching features
  - Desire category matching features

Historical click through log

user: \(<CTR_{p1}, CTR_{p2}, \ldots, CTR_{pn}>\)

user: \(<CTR_{c1}, CTR_{c2}, \ldots, CTR_{c5}>\)

ad: \(<0,0,\ldots,0,1,0,\ldots,1,0>\)
desire space

ad: \(<0,0,1,0,1>\)
desire category space
Roadmap

• Motivations
• Data Analysis on User Psychological Desires
• Discovering User Psychological Desire from Ads
• Click Prediction Modeling
• Experimental Evaluations
Experimental Settings

• Data set:
  • A sample of click-through logs in a two-week period from a commercial search engine

<table>
<thead>
<tr>
<th></th>
<th>Ad impressions</th>
<th># of unique ads</th>
<th># of unique queries</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training (1st week)</td>
<td>20.8M</td>
<td>4.3M</td>
<td>2.6M</td>
</tr>
<tr>
<td>Testing (2nd week)</td>
<td>19.8M</td>
<td>5.3M</td>
<td>2.5M</td>
</tr>
</tbody>
</table>

• Compared Methods

<table>
<thead>
<tr>
<th></th>
<th>Relevance features</th>
<th>Historical click features</th>
<th>Desire pattern features</th>
<th>Desire category features</th>
</tr>
</thead>
<tbody>
<tr>
<td>HF (base)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HF-RF</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HF-DPF</td>
<td></td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>HF-DPLF</td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>HF-RF-DPF</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>HF-RF-DPLF</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>
Experimental Settings

• Evaluation Metrics
  • Relative Information Gain (RIG) (T. Graepel, et al. ICML 2010)

\[
\text{RIG} = \frac{\text{LogScore} + \text{Entropy(CTR)}}{\text{Entropy(CTR)}} = 1 + \frac{\text{NormalizedLogScore}}{\text{Entropy(CTR)}}
\]

\[
\text{LogScore} = \frac{1}{N} \sum_i y_i \ln p_i + (1 - y_i) \ln(1 - p_i)
\]

\[
\text{Entropy(CTR)} = -\text{CTR} \ln \text{CTR} - (1 - \text{CTR}) \ln(1 - \text{CTR}), \text{ with } \text{CTR} = \frac{1}{N} \sum_i y_i
\]

• Where
  - \( p_i \) are the pClick scores
  - \( y_i \) values are the Click=1/NoClick=0 labels.

  > RIG@ML-1 and AllPositionRIG
  - Since \( p_i = 0 \) and \( p_i = 1 \) values can produce infinity values, \( p_i \) is clamped to lie between \( p_i \in [\varepsilon, 1 - \varepsilon] \), where \( \varepsilon = 10^{-5} \). Both \( p_i \) and \( c_i \) values are from the “test” set.

• Simulated Click-through rate (CTR)
  • Replay-based simulation: re-rank ads and use real clicks as ground-truth
Overall Performance

<table>
<thead>
<tr>
<th>Method</th>
<th>Relative gain in RIG</th>
<th>Relative gain in CTR</th>
</tr>
</thead>
<tbody>
<tr>
<td>HF-RF</td>
<td>2%</td>
<td>3%</td>
</tr>
<tr>
<td>HF-DPF</td>
<td>3%</td>
<td>4%</td>
</tr>
<tr>
<td>HF-DPLF</td>
<td>4%</td>
<td>5%</td>
</tr>
<tr>
<td>HF-RF-DPF</td>
<td>5%</td>
<td>6%</td>
</tr>
<tr>
<td>HF-RF-DPLF</td>
<td>6%</td>
<td>7%</td>
</tr>
</tbody>
</table>
Overall Performance

User desire features can lead to significant improvement on click prediction.
Overall Performance

- User desire features can lead to significant improvement on click prediction
- Desire category features are good complements to desire pattern features
  - It can reduce the sparsity of desire features for individual ads
Impacts on Ads with Rich v.s. Rare History

- Rich history set:
  - Relevance features may not very beneficial
  - Since advertisers may adjust ad text, it is beneficial to always leverage updated desire patterns for click prediction

- Rare history set:
  - Click prediction is mainly based on understanding users’ click intents (why)
  - Relevance features may not indicate users’ potential for consuming
  - User psychological desires can more effectively reflect users’ potential for consuming
Conclusion and Future Work

• Summary
  
  • Asking “why” of user clicks on ads and designing strong features according to the answer
  
  • Connect click prediction with user behavior analysis
  
  • Embrace user psychological desire in ad click prediction
  
  • Promising experimental results over a large scale data set from real world

• Future Work
  
  • Context-aware user psychological desire
    ▪ If user desire is dependent with queries or other kinds of search context
  
  • Structured user desire
    ▪ If the hierarchical relationship of user psychological desire can be leveraged in click prediction
  
  • Temporal psychological desire
    ▪ Modeling users’ temporal psychological desire and detecting their emerging interests in terms of desire at real-time
Thanks!

Taifeng Wang\textsuperscript{1}, Jiang Bian\textsuperscript{1}, Shusen Liu\textsuperscript{2}, Yuyu Zhang\textsuperscript{3}, Tie-Yan Liu\textsuperscript{1}

\textsuperscript{1}Microsoft Research Asia
\textsuperscript{2}South China University of Technology
\textsuperscript{3}Chinese Academy of Science