

DATA SCIENCE & AD:TECH

MIKE SCHUMACHER 2018-11

AGENDA

- Quick Bio
- Ad:Tech 101
- DS Application – Propensity Ranking
- DS Application – Purchase Likelihood
- DS Application – Clustering
- Summary

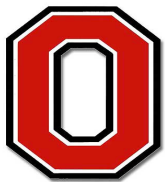
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QUICK BIO



Economics + Statistics



MS, Statistics



(Analyst) Predictive Modeling, Design of Experiment, BI



(Director) Managed ~10, Large Scale Predictive Modeling, Causal Inference



(VP) Managed ~25, Machine Learning, Optimization Algo's, Consumer Insights



(VP) Manage ~50, Machine Learning, College Recruiting, Tech/Tools

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- Enables “free” Social Networking, News, Search, Music, etc.
 - 84% of Google Revenue is Advertising
 - 90% of Facebook Revenue is Advertising
- Ad:Tech Attempts to Connect Consumers With Relevant Ads
 - More effective ads
 - Better consumer experience

MARKETER



PUBLISHER

CONSUMER



Demo

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APPLIED EXAMPLES - APP INSTALLS



Business Question:

Which Facebook users are most likely to install Doodle Jump?

APPLIED EXAMPLES - APP INSTALLS

Naive Bayes: http://en.wikipedia.org/wiki/Naive_Bayes_classifier

$$p(C_k | x_1, \dots, x_n) = \frac{1}{Z} p(C_k) \prod_{i=1}^n p(x_i | C_k)$$

$C_k = 1$ is “Class 1”, meaning the app *was* installed for a randomly selected set of users.

x_1 = predictive variable #1 (number of game app’s installed)

x_2 = predictive variable #2 (age of device owner)

Z = is likelihood of feature set (x_i ’s)

In English: What is the probability of having Doodle Jump installed given your age and number of game apps?

APPLIED EXAMPLES - APP INSTALLS

Let's consider the ratio of the probabilities under each class. In addition:

- ... take the log (monotonic)
- ... use Bayes rule (flip the conditional)
- ... and assume independence (*Naive* Bayes.)

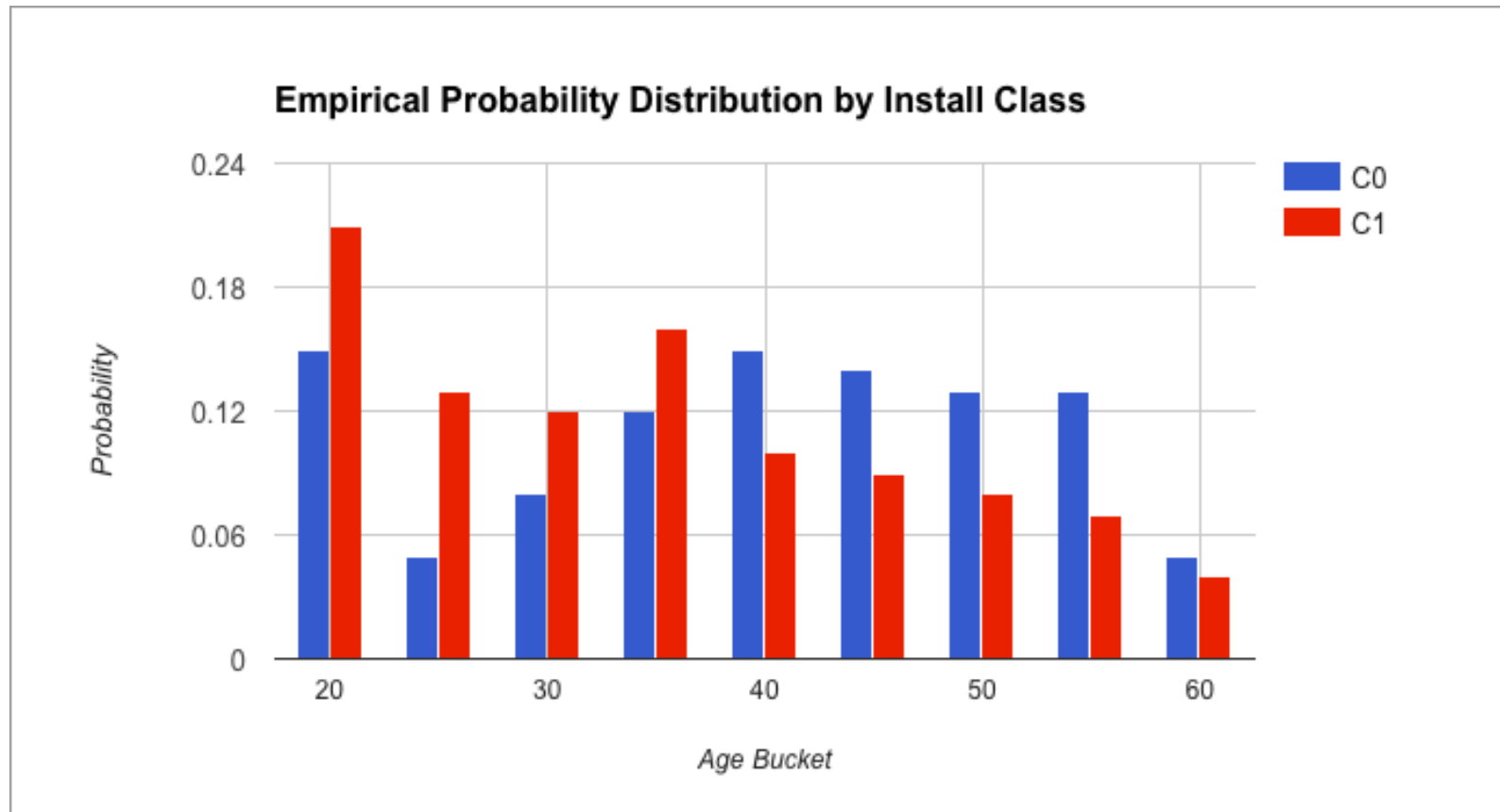
$$\ln \left(\frac{P(C_1|x_1, x_2)}{P(C_0|x_1, x_2)} \right) \propto \sum_{i=1}^2 \ln \left(\frac{P(x_i|C_1)}{P(x_i|C_0)} \right)$$

Now we can sum the log-odds which can be empirically calculated from “big data.”

In English: We can evaluate each variable (age, # of apps) on its own after splitting the data into “Doodle Jump” vs “No DJ”

APPLIED EXAMPLES - APP INSTALLS

Example: Predictive Variable Age

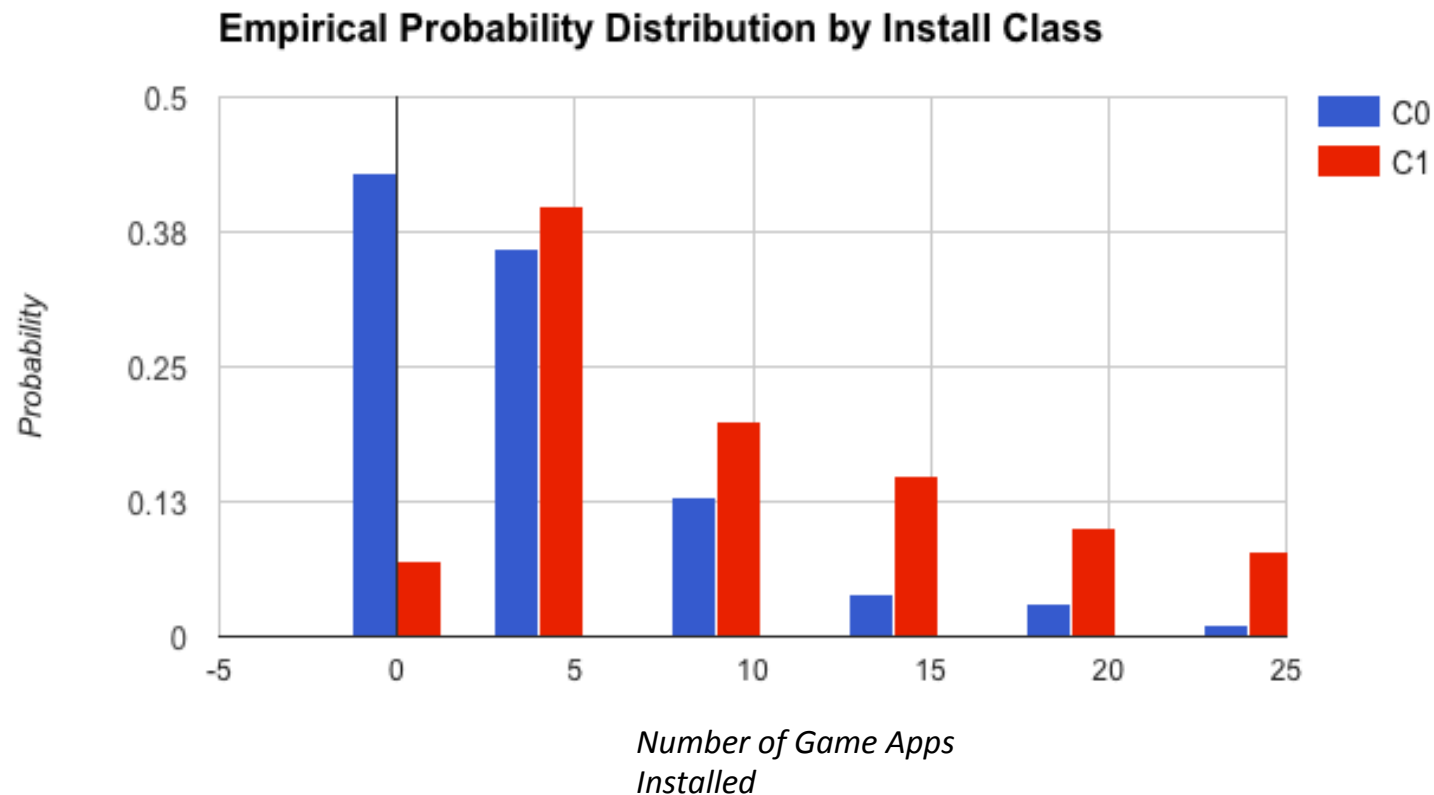


$$\ln \left(\frac{P(x_1|C_1)}{P(x_1|C_0)} \right)$$

If “Ron” is in age bucket 25, his ‘term score’ for age is the natural log of 13% divided by 5%, or 0.95.

APPLIED EXAMPLES - APP INSTALLS

Example: Predictive Variable Number of Games Installed



$$\ln \left(\frac{P(x_2|C_1)}{P(x_2|C_0)} \right)$$

If “Ron” has 25 game apps installed, his ‘term score’ for “game apps” is the natural log of 8% divided by 1%, or 2.1.

APPLIED EXAMPLES - APP INSTALLS

$$\ln \left(\frac{P(C_1|x_1, x_2)}{P(C_0|x_1, x_2)} \right) \propto \sum_{i=1}^2 \ln \left(\frac{P(x_i|C_1)}{P(x_i|C_0)} \right)$$

Score “Ron” who has 25 games installed and is age 25:

User Score = Age_Term_Score + Game_Apps_Age_Score

User Score = 0.95 + 2.10 = 3.05

Compare this score to peers... select the best ranking users (no probabilities.)

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APPLIED EXAMPLES - PURCHASE PREDICTION



If a random user shows up on a webpage, what is the probability that he/she will buy from REI in the next 30 days?

APPLIED EXAMPLES - PURCHASE PREDICTION



If a random user shows up on a webpage, what is the probability that he/she will buy from REI in the next 30 days?

ANS: 0.000015%

APPLIED EXAMPLES - PURCHASE PREDICTION

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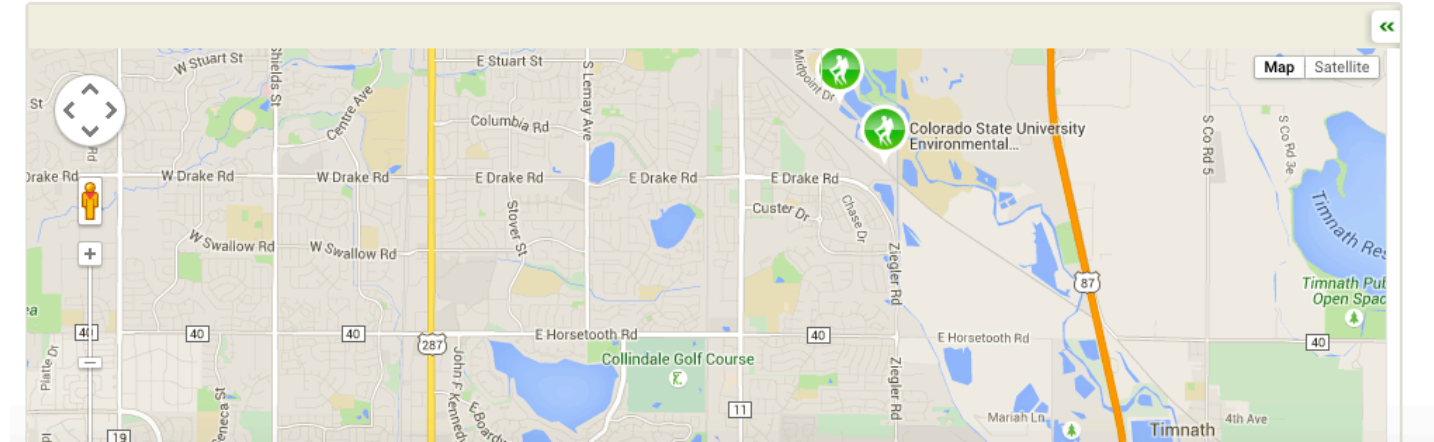
Trails » Trail Finder » Search for Trails by Map

But should we assume 0.000015% for this user?

Search for Trails by Map

Enter City Select a State + Zoom to City Filter Activity by: Show all activities Advanced Options

Map Satellite



APPLIED EXAMPLES - PURCHASE PREDICTION

Decision Tree Splitting Criteria - Information Value

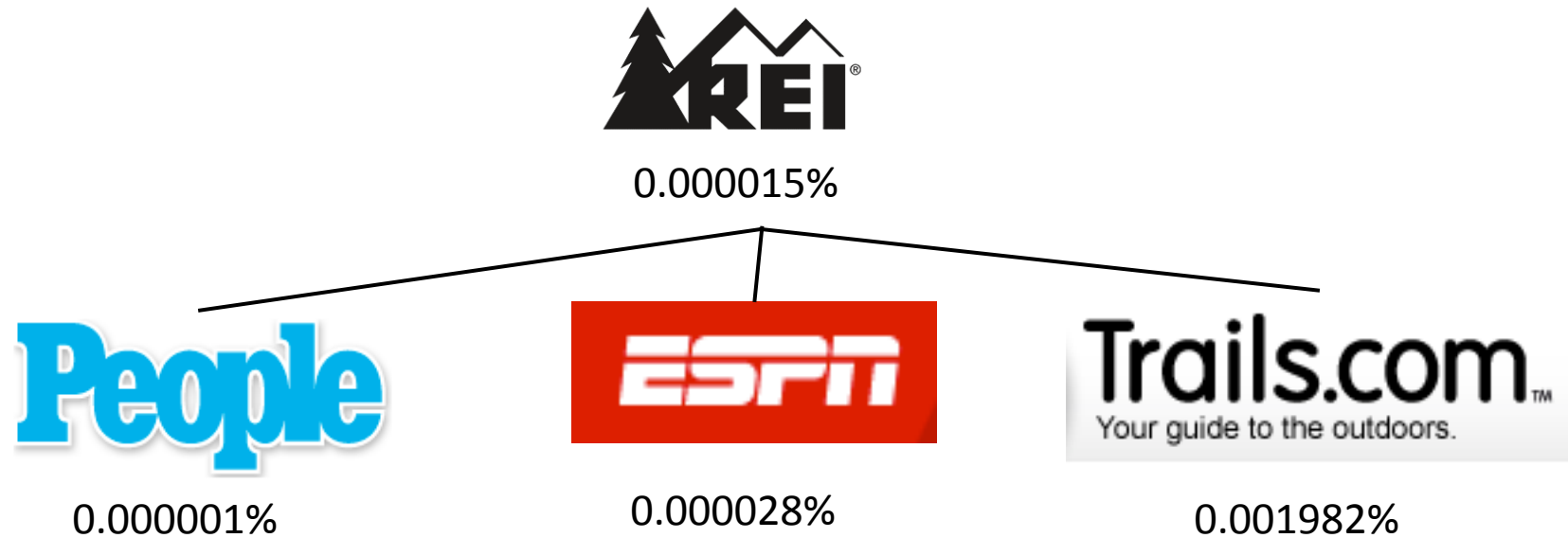
URL	Perc_Buy	Perc_NoBuy	Woe	IV
people	4%	8%	-0.693	0.028
trails	7%	2%	1.253	0.063
espn	3%	2%	0.405	0.004
Other	60%	88%	-0.383	0.107
				0.202
Income	Perc_Buy	Perc_NoBuy	Woe	IV
\$	20%	35%	-0.560	0.084
\$\$\$	60%	50%	0.182	0.018
\$\$\$\$\$	20%	15%	0.288	0.014
				0.117

$$WOE_i = \ln \left(\frac{BuyPerc_i}{NoBuyPerc_i} \right) \quad i = 1, 2, \dots, n$$

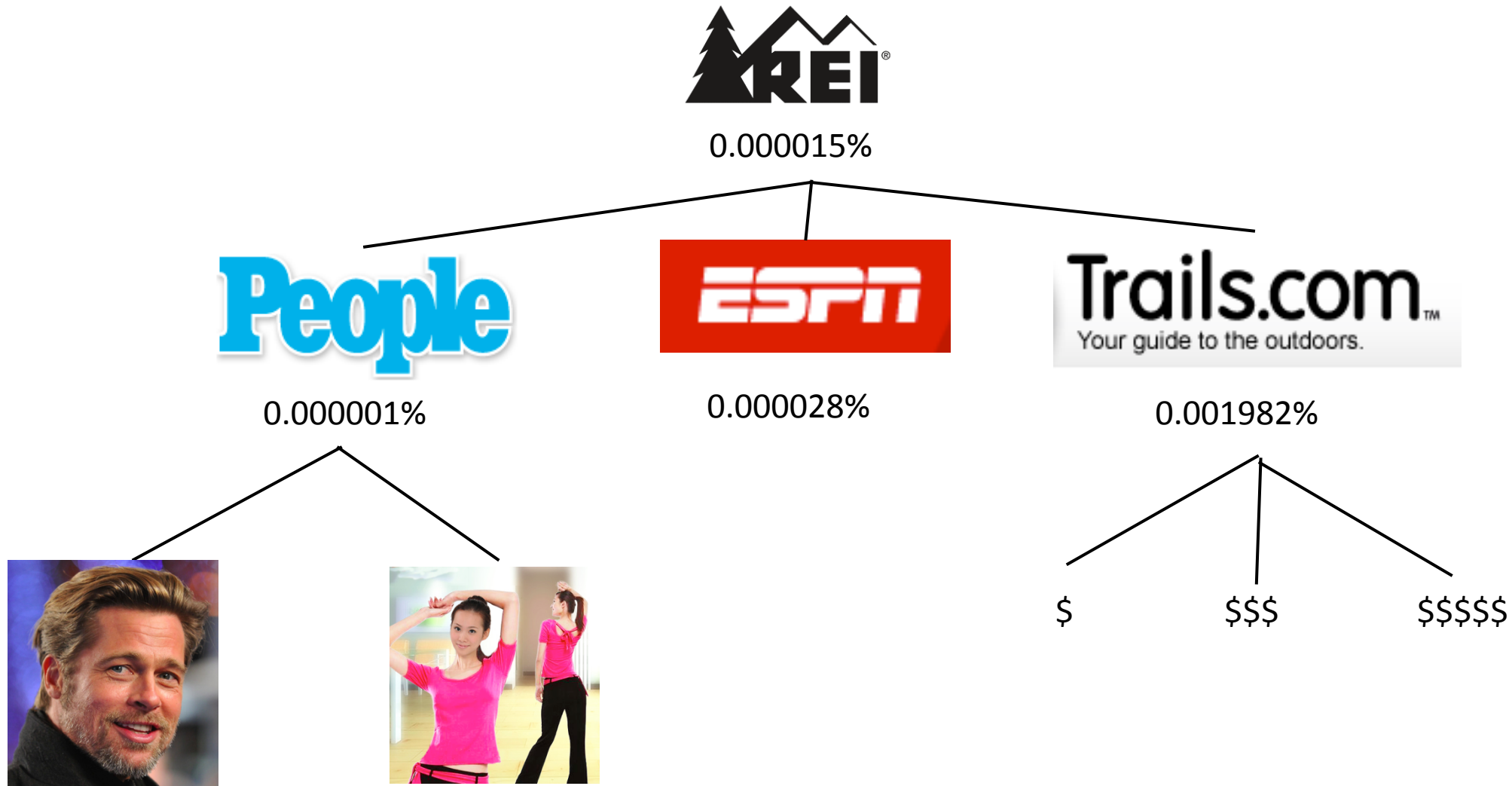
$$IV = \sum_{i=1}^n ((BuyPerc_i - NoBuyPerc_i) * WOE_i)$$

Calculate the IV for each explanatory variable and determine the best predictor.

APPLIED EXAMPLES - PURCHASE PREDICTION



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APPLIED EXAMPLES - CLUSTERING



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THANK YOU!



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