Class 15a: Predicting Attrition

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MKTG 482: Customer Analytics Kellogg School of Management

Customer Analytics Course Structure

Customer Centric Marketing

Customer Analytics and Al Overview (Class 1)
 Al and Analytics,

Why Customer Analytics and Al Needs Customer Centricity

Getting Ready for Analytics

- Using R for Customer Analytics and AI (Class 2)
- Statistics Review (Class 3)

Targeting Customers for Acquisition and Development

- Predicting Response with RFM analysis (Class 4)
- Case Analysis: "Tuango: RFM Analysis for Mobile App Push Messaging" (Class 5)
 Lift and Gains
- Predicting Response with Logistic Regression (Class 6)
- Predicting Response with Neural Networks (Class 7)
- Using Neural Networks for Customer Analytics and AI (Class 8)
 - Training Machine Learning Models
- Case Analysis: Intuit QuickBooks Upgrade: Moving to the Cloud (Class 9)
- Predicting Response with Tree Methods (Class 10)

Targeting based on Incrementality

- From Propensity to Uplift (Class 11)
- The Causality Checklist (Class 12)
- Case Analysis: Creative Gaming Uplift Modeling (Class 13)
- Hyper-Personalization: Next-Product-to-Buy Models (Class 14)

Retaining Customers

- Predicting Attrition (Class 15)
- Linking Analytics with a Business Outcomes Model (Class 16)
- Case Analysis: "S-Mobile: Churn Management" (Class 17)
 From Prediction to Action

Selecting the Right Offers

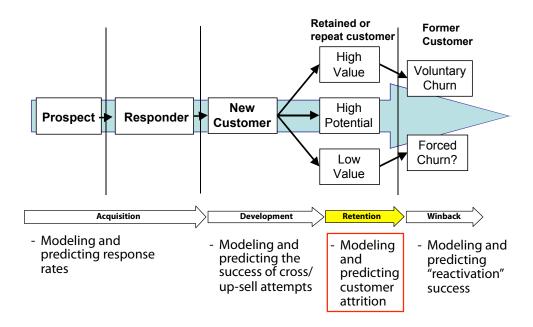
- Design of Experiments / Multivariate Testing (Class 18)
- Case Analysis: "Capital One: Information-Based Credit Card Design" (Class 19)

Scaling Analytics

Scaling Analytics in Practice (Class 20)
Course Wrap-up

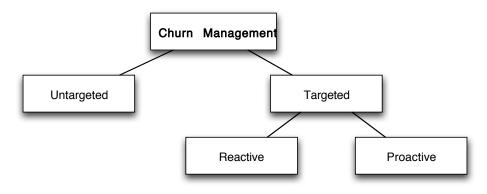
We now consider how we can use information based marketing to postpone the end of the customer lifecycle

APPLICATIONS OF PREDICTIVE TECHNIQUES



Retention strategies (churn management) have historically been untargeted

APPROACHES TO CHURN MANAGEMENT



- Improvements in product quality
- Mass advertising
- Contact customers at the time or after he/she churns
- Contact customers before he/she churns

How can predictive analytics help?

CONTRIBUTIONS OF PREDICTIVE ANALYTICS

- Predict individual churn probabilities
- Example:
 - Overall (baseline) churn rate is 20% per year
 - With model identify customers who have 30%, 40%, etc. churn rate
- Determine which factors lead to the highest success rate, i.e. are most likely to change attrition behavior
- Example:
 - Model reveals that customers with a tech support wait time exceeding 5 minutes are more likely to leave
 - Give priority to customers who are likely to churn

We need attrition data to develop a retention model

REQUIRED DATA FOR RETENTION MODEL

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:			·
Customer 5:	Demographics	•Targeted Advertising •	0
Customer 4:	Demographics	Marketing Actions • Offers	1
Customer 3:	Demographics	•	0
Customer 2:	Demographics	Communications Characteristics	0
Customer 1:	Demographics	Consumer Behavior • Purchases/Usage	1
		t-4 t-3 t-2 t-1	t Time

Independent or "Predictor" Variables Dep. Variable: Did the customer churn?

We will design a churn management program for Netflix

NETFLIX EXAMPLE*



- Largest DVD by mail provider
- 4 MM customers 2006
- High recurrent revenue
- Revenue sharing with movie studios, pay \$1.5 per rental

Membership Plans

- 8 at-a-time (Unlimited) for \$47.99
- Unlimited rentals up to 8 movies out at a time for a flat monthly fee of \$47.99.

7 at-a-time (Unlimited) for \$41.99
 Unlimited rentals - up to 7 movies out at a time for a flat monthly fee of \$41.99.

6 at-a-time (Unlimited) for \$35.99

Unlimited rentals - up to 6 movies out at a time for a flat monthly fee of \$35.99.

- 5 at-a-time (Unlimited) for \$29.99 Unlimited rentals - up to 5 movies out at a time for a flat monthly fee of \$29.99.
- 4 at-a-time (Unlimited) for \$23.99

Unlimited rentals - up to 4 movies out at a time for a flat monthly fee of \$23.99.

You are currently on this plan:

- 3 at-a-time (Unlimited) for \$17.99
- Unlimited rentals up to 3 movies out at a time for a flat monthly fee of \$17.99.
- O 2 at-a-time (Unlimited) for \$14.99

Unlimited rentals - up to 2 movies out at a time for a flat monthly fee of \$14.99.

1 at-a-time (Unlimited) for \$9.99

Unlimited rentals - up to 1 movie out at a time for a flat monthly fee of \$9.99.

3 at-a-time is the most popular plan

PLAN POPULARITY AND USAGE

Plan	Montly Price (\$)	Customers	Av. Mo. Usage
1	9.99	5.2%	2.3
2	14.99	10.6%	3.8
3	17.99	53.6%	5.1
4	23.99	20.1%	6.1
5	29.99	3.2%	7.3
6	35.99	1.8%	8.5
7	41.99	1.0%	11.1
8	47.99	4.5%	13.3
		100.0%	

CHURN PROBLEM

- Churn rate 1.34% per month
 - $(=1-(1-0.0134)^12)$ = 14.95% per year
- After 4 years, 50% of a cohort has churned

^{*}The numbers used in this example are hypothetical and should not be considered an accurate reflection of churn at Netflix

We will develop a proactive churn management program

CHURN MANAGEMENT STEPS

- 1. Develop a model to **predict** customer churn
- 2. Use model to **understand** main drivers of churn
- 3. Use insights to **develop** actions/offers/incentives
- 4. Estimate the **impact** of these actions/offers/incentives on the probability of churn
- 5. Decide which actions/offers/incentives to target to which customers
- 6. **Evaluate** the economics

We have a rich set of variables to predict attrition

NETFLIX DATA

- Dependent variable:
 Did customer cancel Netflix in January 2006?
- Independent variables:

Predictor Variable	Dummy	Mean	St. Dev.	Min	Max
Current plan (# concurrent DVDs)	0	3.37	1.40	1	8
Total # of Movies	0	33.87	21.94	0	141
Av. Monthly Change in # Movies	0	0.20	0.78	-7	9
Average Shipping Delay	0	0.45	0.62	0	8
Lowest 10% in #movies for plan	1	0.10	0.30	0	1.000
# Reported scratched	0	0.60	0.84	0	5
# Reported missing	0	0.30	0.41	0	6
Moved in last 6 months?	1	0.12	0.33	0	1
Average movie rating	0	3.53	0.83	2.1	4.96
Age 60+	1	0.18	0.39	0	1
Called Cust Service to request HD-DVD	1	0.08	0.27	0	1
Resulted from a referral	1	0.27	0.45	0	1

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The coefficients from the model suggest that a number of factors drive people away

RESULTS LOGISTIC REGRESSION

Variable	Estimate	Std. Error	z-value	p-value
Current plan (# concurrent DVDs)	0.048	0.044	1.092	0.275
Total # of Movies	0.002	0.002	1.412	0.158
Av. Monthly Change in # Movies	-0.386	0.164	-2.357	0.018
Average Shipping Delay	0.233	0.076	3.076	0.002
Lowest 10% in #movies for plan	0.770	0.285	2.706	0.007
# Reported scratched	0.351	0.105	3.330	0.001
# Reported missing	0.191	0.079	2.423	0.015
Moved in last 6 months?	0.113	0.124	0.915	0.360
Average movie rating	0.020	0.010	1.951	0.051
Age 60+	-0.197	0.066	-2.968	0.003
Called Cust Service to request HD	0.523	0.252	2.075	0.038
Resulted from a referral	-0.311	0.117	-2.656	0.008

Next, we determine the relative importance of factor for predicting churn

PREDICTORS BY IMPORTANCE

variable	factor	var_imp	var_imp_lower	var_imp_upper	p-value
Lowest 10% in #movies for plan	1	0.770	0.212	1.328	0.007
Av. Monthly Change in # Movies	0	-0.602	-1.102	-0.101	0.018
# Reported scratched	0	0.591	0.243	0.938	0.001
Called Cust Service to request HD	1	0.523	0.029	1.017	0.038
Resulted from a referral	1	-0.311	-0.540	-0.081	0.008
Average Shipping Delay	0	0.291	0.106	0.476	0.002
Age 60+	1	-0.197	-0.327	-0.067	0.003
# Reported missing	0	0.158	0.030	0.285	0.015
Current plan (# concurrent DVDs)	0	0.133	-0.106	0.371	0.275
Moved in last 6 months?	1	0.113	-0.129	0.356	0.360
Total # of Movies	0	0.105	-0.041	0.251	0.158
Average movie rating	0	0.033	0.000	0.066	0.051

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What should Netflix do to reduce customer churn?

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- Ideas?

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- For each predictor in turn, consider:
 - ▶ Is this predictor actionable?
 - ▶ If so, where in the customer lifecycle would be the place the act?
 - ▶ And what action / offer would you make at that place in the customer lifecycle?

CHURN MANAGEMENT STEPS

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There are two ways to predict the effect of an action/incentive/offer on the predicted probability of churn

PREDICTING IMPACT

- 1. Simulate the effect of a churn driver by changing the value of the variable and using the estimated logistic regression model to obtain new churn predictions
- 2. Test the action/incentive/offer in the field

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R Demo

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To ensure that a test feasible, answer these three questions

QUESTIONS	WATCH OUT
1. Do I have the technology or capability of randomly targeting units (e.g., customers, channel partners, etc.)?	 "Close enough" randomization Is it possible? (e.g., do business constraints limit random assignment of offers)

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2. Will my experiment cause spillovers among customers?	 Customers may talk to each other, share information Fairness/equity issues may arise if the exp. becomes common knowledge 					
3. What is the size of my overall sample for the experiment?	Precision requirementsOthers to be discussed in R demo					

Q: How large does my sample need to be? A: How precisely do you want to estimate the proportion?

REVIEW

- Recall the the formula the 95% confidence interval for a proportion:

$$\hat{p} \pm 1.96\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$

- The precision (as assessed by the interval halfwidth) is $1.96\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$
- The confidence level of 95% determines $z_{1-\frac{0.05}{2}}=1.96$
- So, for a desired level of precision and confidence, we can set the sample size via

$$hw = 1.96\sqrt{\frac{\hat{p}(1-\hat{p})}{n}}$$
 \Rightarrow $n = \frac{1.96^2\hat{p}(1-\hat{p})}{hw^2}$

R Demo

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PREDICTING IMPACT

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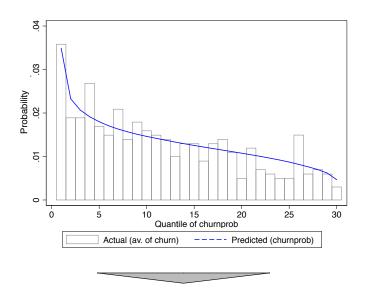
In the S-mobile case, which method might you choose for which churn action/incentive/offer?

CHURN MANAGEMENT STEPS

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Given an estimate of the effect of a churn action/incentive/ offer, how should the absolute churn probability factor in?

PREDICTED CHURN IN REPRESENTATIVE SAMPLE



In the S-mobile case, consider how a customer's absolute churn probability should affect the selection of that customer for churn actions

A plan specifies an action/incentive/offer and a rule for selecting customers

EXAMPLE OF CHURN PLAN FOR NETFLIX EXAMPLE

- Action: Eliminate average shipping delay
 Targeting rule: None, affects all customers
 Expected churn benefit: Baseline churn: 1.34%, projected churn: 1.25%
- Action: Offer consumer plan downgrade
 Targeting rule: Consumer is in lowest 10% of usage in their respective plan
 Consumer has above average total churn probability
 Expected churn benefit: Baseline churn 3.2%, projected churn 2.0%

3. ...

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Targeting rule: Consumer is in lowest 10% of usage in their respective plan Consumer has above average total churn probability

Expected churn benefit: Baseline churn 3.2%, projected churn 2.0%

3. ...

How do we link churn to business outcome metrics?

What is it worth to eliminate average shipping delays to our company (for 3 at-a-time customer)?

LTV FOR 3 AT-A-TIME DVD PLAN

								_
	Now	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Baseline churn: 1.34%
Revenue	\$0	\$216	\$216	\$216	\$216	\$216	\$216	Yearly: 1-(1-0.0134)^12 = 14.95%
Product/Service Cost	\$0	\$122	\$122	\$122	\$122	\$122	\$122	
Action/Offer/Incentive Cost	\$0	\$0	\$0	\$0	\$0	\$0	\$0	Projected churn: 1.25%
Profit	\$0	\$93	\$93	\$93	\$93	\$93	\$93	Yearly: 1-(1-0.0125)^12 = 14.0%
Prob. active at end of period	100%	85%	72%	62%	52%	45%	38%	
Prob. active within period	100%	93%	79%	67%	57%	48%	41%	
Expected Profit	\$0	\$86	\$74	\$63	\$53	\$45	\$38	
Present Value of Exp. Profit	\$0	\$82	\$64	\$49	\$38	\$29	\$23	\$286
	Now	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	
Revenue	\$0	\$216	\$216	\$216	\$216	\$216	\$216	*
Product/Service Cost	\$0	\$122	\$122	\$122	\$122	\$122	\$122	
Action/Offer/Incentive Cost	\$0	\$0	\$0	\$0	\$0	\$0	\$0	Value of Churn Program:
Profit	\$0	\$93	\$93	\$93	\$93	\$93	\$93	\$7 per subscriber
Prob. active at end of period	100%	86%	74%	64%	55%	47%	40%	1
Prob. active within period	100%	93%	80%	69%	59%	51%	44%	/
Expected Profit	\$0	\$87	\$75	\$64	\$55	\$48	\$41	
Present Value of Exp. Profit	\$0	\$83	\$65	\$51	\$40	\$31	\$24	\$293

Suppose we could eliminate these delays with a one-time payment

LTV FOR 3 AT-A-TIME DVD PLAN

	Now	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Baseline churn: 1.34%
Revenue	\$0	\$216	\$216	\$216	\$216	\$216	\$216	Yearly: 1-(1-0.0134)^12 = 14.95%
Product/Service Cost	\$0	\$122	\$122	\$122	\$122	\$122	\$122	
Action/Offer/Incentive Cost	\$0	\$0	\$0	\$0	\$0	\$0	\$0	Projected churn: 1.25%
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Revenue	\$0	\$216	\$216	\$216	\$216	\$216	\$216	A
Product/Service Cost	\$0	\$122	\$122	\$122	\$122	\$122	\$122	6
Action/Offer/Incentive Cost	\$7	\$0	\$0	\$0	\$0	\$0	\$0	Can spend up to: \$7 per subscriber now
Profit	-\$7	\$93	\$93	\$93	\$93	\$93	\$93	Typer subscriber flow
Prob. active at end of period	100%	86%	74%	64%	55%	47%	40%	A
Prob. active within period	100%	93%	80%	69%	59%	51%	44%	
Expected Profit	-\$7	\$87	\$75	\$64	\$55	\$48	\$41	
Present Value of Exp. Profit								

However eliminating average shipping delays is perhaps better modeled as on ongoing cost

LTV FOR 3 AT-A-TIME DVD PLAN

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			100.1		icai +	100.0	icai o	baseline chum: 1.54%
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Product/Service Cost	\$0	\$122	\$122	\$122	\$122	\$122	\$122	
Action/Offer/Incentive Cost	\$0	\$0	\$0	\$0	\$0	\$0	\$0	Projected churn: 1.25%
Profit	\$0	\$93	\$93	\$93	\$93	\$93	\$93	Yearly: 1-(1-0.0125)^12 = 14.0%
Prob. active at end of period	100%	85%	72%	62%	52%	45%	38%	
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Revenue	\$0	\$216	\$216	\$216	\$216	\$216	\$216	*
Product/Service Cost	\$0	\$122	\$122	\$122	\$122	\$122	\$122	
Action/Offer/Incentive Cost	\$0.0	\$2.3	\$2.3	\$2.3	\$2.3	\$2.3	\$2.3	Can spend up to:
Profit	\$0	\$91	\$91	\$91	\$91	\$91	\$91	\$2.3 per year per subscriber
Prob. active at end of period	100%	86%	74%	64%	55%	47%	40%	A
Prob. active within period	100%	93%	80%	69%	59%	51%	44%	
Expected Profit	\$0	\$85	\$73	\$63	\$54	\$46	\$40	
Present Value of Exp. Profit	\$0	\$81	\$63	\$49	\$39	\$30	\$24	\$286

What we can spend depends on the type of customer (now consider 4-at-a-time plan)

LTV FOR 4 AT-A-TIME DVD PLAN

	Now	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Baseline churn: 1.34%
Revenue	\$0	\$288	\$288	\$288	\$288	\$288	\$288	Yearly: 1-(1-0.0134)^12 = 14.95%
Product/Service Cost	\$0	\$146	\$146	\$146	\$146	\$146	\$146	
Action/Offer/Incentive Cost	\$0	\$0	\$0	\$0	\$0	\$0	\$0	Projected churn: 1.25%
Profit	\$0	\$142	\$142	\$142	\$142	\$142	\$142	Yearly: 1-(1-0.0125)^12 = 14.0%
Prob. active at end of period	100%	85%	72%	62%	52%	45%	38%	
Prob. active within period	100%	93%	79%	67%	57%	48%	41%	
Expected Profit	\$0	\$131	\$111	\$95	\$81	\$69	\$58	
Present Value of Exp. Profit	\$0	\$125	\$97	\$75	\$58	\$45	\$35	\$433
	Now	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	
Revenue	\$0	\$288	\$288	\$288	\$288	\$288	\$288	``
Product/Service Cost	\$0	\$146	\$146	\$146	\$146	\$146	\$146	Can spend up to:
Action/Offer/Incentive Cost	\$0.0	\$3.5	\$3.5	\$3.5	\$3.5	\$3.5	\$3.5	\$3.5 per year per subscriber
Profit	\$0	\$138	\$138	\$138	\$138	\$138	\$138	(was \$2.3 for 3-at-a-time)
Prob. active at end of period	100%	86%	74%	64%	55%	47%	40%	A
Prob. active within period	100%	93%	80%	69%	59%	51%	44%	
Expected Profit	\$0	\$128	\$110	\$95	\$82	\$70	\$60	
Present Value of Exp. Profit	\$0	\$122	\$96	\$75	\$58	\$46	\$36	\$433

A plan specifies an action/incentive/offer and a rule for selecting customers

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Targeting rule: Consumer is in lowest 10% of usage in their respective plan Consumer has above average total churn probability

Expected churn benefit: Baseline churn 3.2%, projected churn 2.0%

What is the benefit of downgrading consumers from the 4 to the 3-at a time plan (usage is 3.1 vs. 6.1)?

LTV FOR 4 AT-A-TIME DVD PLAN

	Now	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Baseline churn: 3.2%
Revenue	\$0	\$288	\$288	\$288	\$288	\$288	\$288	Yearly: 1-(1-0.032)^12 = 32.3%
Product/Service Cost	\$0	\$74	\$74	\$74	\$74	\$74	\$74	
Action/Offer/Incentive Cost	\$0	\$0	\$0	\$0	\$0	\$0	\$0	Projected churn: 2.00%
Profit	\$0	\$214	\$214	\$214	\$214	\$214	\$214	Yearly: 1-(1-0.02)^12 = 21.5%
Prob. active at end of period	100%	67.7%	45.8%	31.0%	21.0%	14.2%	9.6%	
Prob. active within period	100%	84%	57%	38%	26%	18%	12%	
Expected Profit	\$0	\$179	\$121	\$82	\$56	\$38	\$25	
Present Value of Exp. Profit	\$0	\$171	\$105	\$65	\$40	\$24	\$15	\$420
								.
	Now	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	
Revenue	\$0	\$216	\$216	\$216	\$216	\$216	\$216	*
Product/Service Cost	\$0	\$74	\$74	\$74	\$74	\$74	\$74	Value of Churn Program:
Action/Offer/Incentive Cost	\$0	\$0	\$0	\$0	\$0	\$0	\$0	Loss of \$55 per subscriber
Profit	\$0	\$141	\$141	\$141	\$141	\$141	\$141	-> don't implement
Prob. active at end of period	100%	78%	62%	48%	38%	30%	23%	1
Prob. active within period	100%	89%	70%	55%	43%	34%	27%	/
Expected Profit	\$0	\$126	\$99	\$78	\$61	\$48	\$38	
Present Value of Exp. Profit	\$0	\$120	\$86	\$61	\$44	\$31	\$22	\$365

CHURN MANAGEMENT STEPS

- 1. Develop a model to **predict** customer churn
- 2. Use model to understand main drivers of churn
- 3. Use insights to **develop** actions/offers/incentives
- 4. Estimate the **impact** of these actions/offers/incentives on the probability of churn
- 5. Decide which actions/offers/incentives to target to which customers
- 6. **Evaluate** the economics

Customer Analytics Course Structure

Customer Centric Marketing

Customer Analytics and Al Overview (Class 1) Al and Analytics,

Why Customer Analytics and Al Needs Customer Centricity

- Getting Ready for Analytics

 Using R for Customer Analytics and AI (Class 2)
- Statistics Review (Class 3)

Targeting Customers for Acquisition and Development

- Predicting Response with RFM analysis (Class 4)
- Case Analysis: "Tuango: RFM Analysis for Mobile App Push Messaging" (Class 5) Lift and Gains
- Predicting Response with Logistic Regression (Class 6)
- Predicting Response with Neural Networks (Class 7)
 Using Neural Networks for Customer Analytics and AI (Class 8) Training Machine Learning Models
- Case Analysis: Intuit QuickBooks Upgrade: Moving to the Cloud (Class 9)
- Predicting Response with Tree Methods (Class 10)

- Targeting based on Incrementality

 From Propensity to Uplift (Class 11)
- The Causality Checklist (Class 12)
- Case Analysis: Creative Gaming Uplift Modeling (Class 13)
- Hyper-Personalization: Next-Product-to-Buy Models (Class 14)

Retaining Customers

- Predicting Attrition (Class 15)
- Linking Analytics with a Business Outcomes Model (Class 16)
- Case Analysis: "S-Mobile: Churn Management" (Class 17) From Prediction to Action

Selecting the Right Offers

Design of Experiments / Multivariate Testing (Class 18)

Case Analysis: "Capital One: Information-Based Credit Card Design" (Class 19)

Scaling Analytics

Scaling Analytics in Practice (Class 20) Course Wrap-up