Class 17b: From Prediction to Action

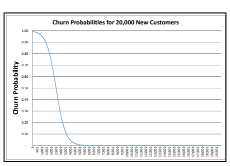
Professor Blake McShane

MKTG 482: Customer Analytics
Kellogg School of Management

We used the predictive analytics churn model in the S-Mobile case in different ways

USES OF PREDICTIVE CHURN MODEL

Use predictions to classify or select consumers



"Identify consumers with high churn probabilities"

Use churn drivers to generate ideas to improve the outcome

- "Lets try to reduce dropped calls"
- "Lets market more to high credit rating customers"
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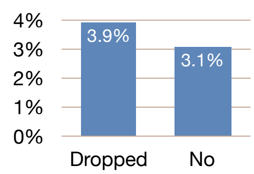
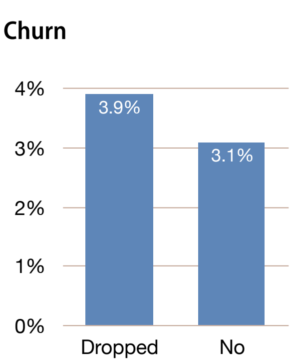
Predict how the outcome would change if you implemented an action



"What is the likely effect of eliminating dropped calls?"

Predictions based on *naturally-occurring* variable values, *don't* require a *causal relationship* between these variables and the outcome for the prediction to be *valid*

In S-Mobile, dropped calls predict churn probabilities



STATEMENT OF FACT

If a consumer has experienced more dropped calls, s/he is more likely to churn

WHY?

- Consumers leave because of dropped calls → **Dropped calls are causal**
- Areas with strong competition experience airwave congestions, leading to many dropped calls

  Independently, competition makes consumers more likely to churn → **Dropped calls are not causal**

Causation is irrelevant for prediction

Predictions based on ***actual*** individual-level variables, ***don't*** require a ***causal relationship*** between these variables and the outcome for the prediction to be ***valid***

Predictions based on ***actual*** individual-level variables, ***don't*** require a ***causal relationship*** between these variables and the outcome for the prediction to be ***valid***

("what if")

Predictions based on ***counterfactual*** individual-level variables, ***do*** require a ***causal relationship*** between these variables and the outcome for the prediction to be ***valid***

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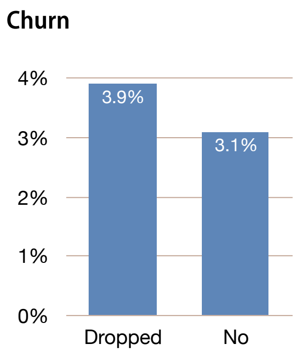

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Would churn for affected customers decrease by 0.8%?

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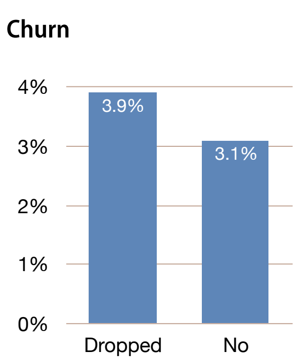

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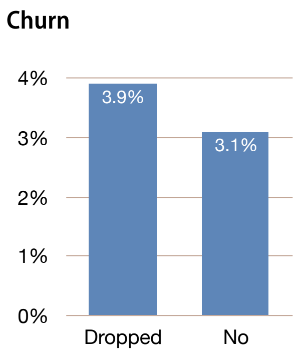

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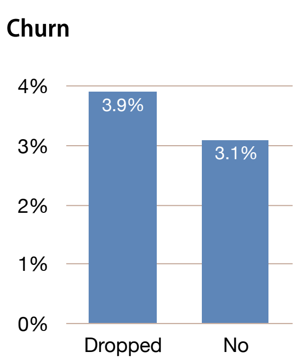

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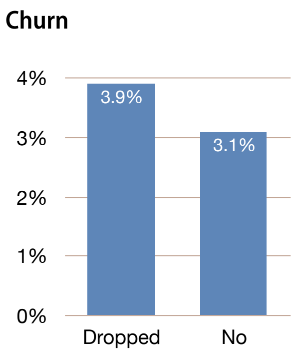
... but if the relationship is not causal, they won't correctly predict the effect of "what-ifs"



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Predictions based on ***naturally-occurring*** variable values, ***<u>don't</u>*** require a ***causal relationship*** between these variables and the outcome for the prediction to be ***valid***

Predictions based on ***"what if"*** variable values, ***<u>do</u>*** require a ***causal relationship*** between these variables and the outcome for the prediction to be ***valid***

Predictive analytics: *Anticipating Outcomes*

Using data **that you have** to predict an **outcome you don't yet know**, using **statistical** or **machine learning** approaches.

> **Examples:** Sales probabilities, inventory levels, customer churn rates, part failures, credit risk ...

Causal analytics: *Changing Outcomes*

Using data that you **have** or **newly create** (e.g. by experimenting) to determine **how** an action ***causes a change*** in the outcome you are predicting.

> **Examples:** How a maintenance call improves uptime, impact of a sales call on conversion, proactive churn interventions, ...

We used the predictive analytics model in different ways

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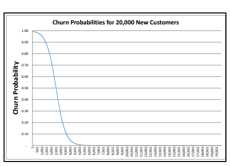

"Identify consumers with high churn probabilities"

Use churn drivers to generate ideas to improve the outcome

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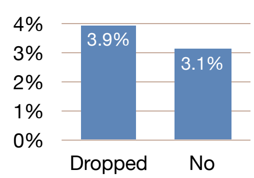
Predict how the outcome would change if you implemented an action



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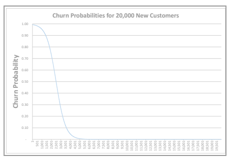

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Predictive **analytics**

Anticipating Outcomes

Causation is irrelevant

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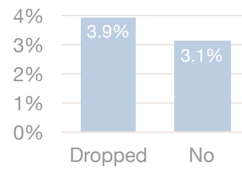

"What is the likely effect of eliminating dropped calls?"

Causal **analytics**

Changing Outcomes

Causation is key

When can *predictive analytics models* cross over into *causal* analytics?

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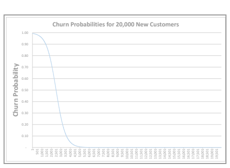

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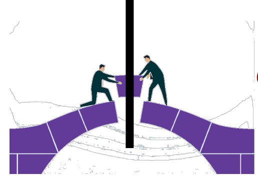

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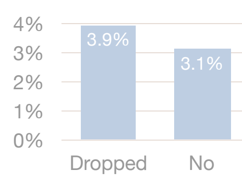

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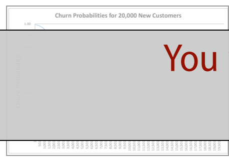

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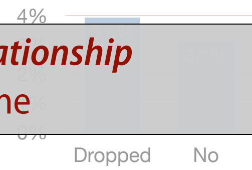
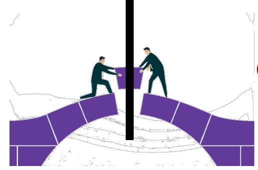


"What is the likely effect of eliminating dropped calls?"

You need to be able to prove a ***causal relationship***
between an action and the outcome

Predictive **analytics**
Anticipating Outcomes

Causation is irrelevant



Causal **analytics**
Changing Outcomes

Causation is key

Proving a causal relationship in a predictive model:

1. **Has this action been previously tried?**
2. **Does the effect of this action on the outcome pass the causality checklist?**
3. **Does the predictive model account for confounds?**
   (matching, diff-in-diff, regression adjustment)

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What does the S-Mobile data tell us about the effect of "surprise and delight" retention measures?

EXAMPLES

- Box of chocolates
- Free premium feature
- 1 month of discounted service
- ...

What if ... we *gave 1 month of discounted service?*
By *how much* would churn decrease?

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The causality checklist helps you uncover bad analytics

CHECK FOR PROBABILISTIC EQUIVALENCE

– Did units get randomly assigned to the groups I am comparing?

IDENTIFY GROUP DRIVERS

– What drivers do you think influenced what groups units ended up in?

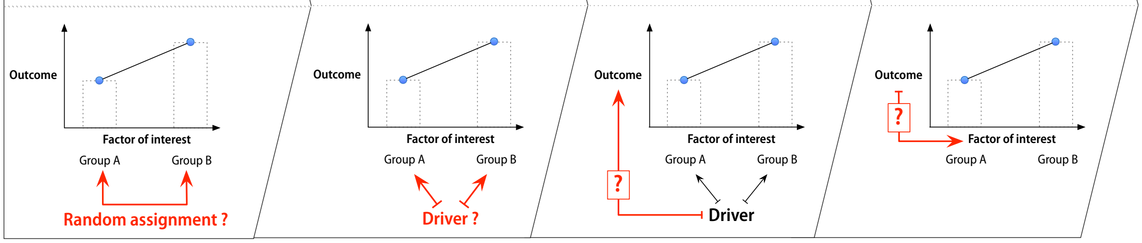
CHECK FOR CONFOUNDS

For each driver:

– Could the driver affect the outcome independently of the group units ended up in?

CHECK FOR REVERSE CAUSALITY

– Could outcome differences have directly caused variation in the factor of interest?



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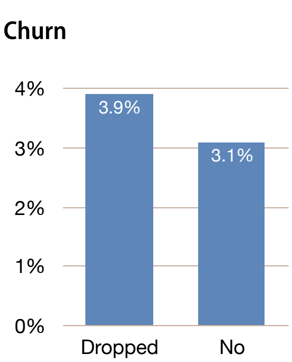

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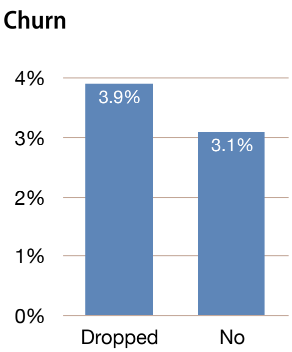

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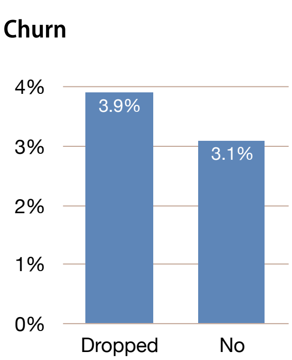

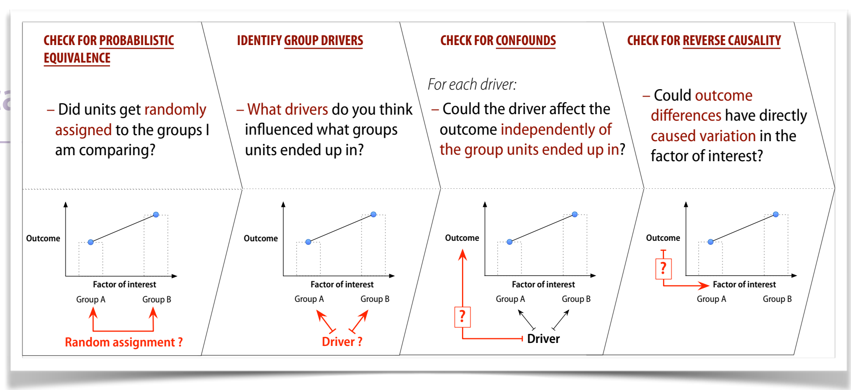

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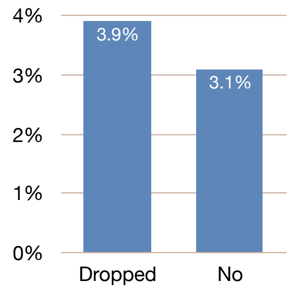

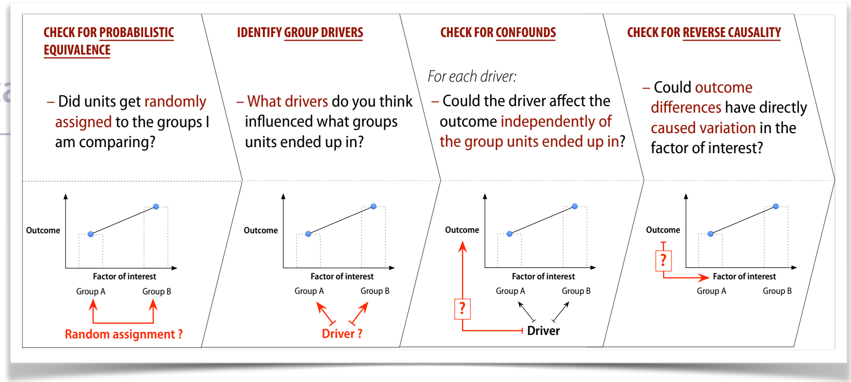

Competition is possible **driver**

Competition is possible **confound**

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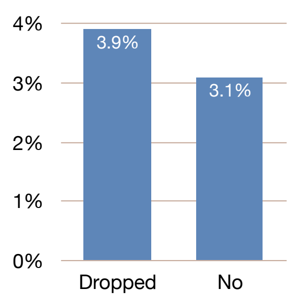

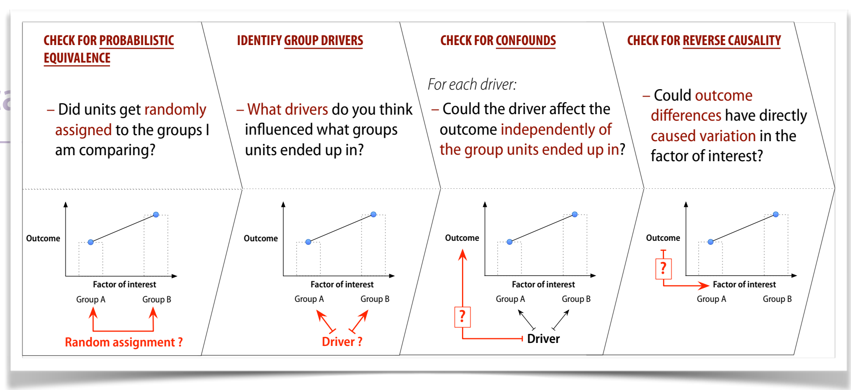

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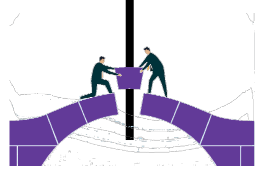
What if … *we eliminated dropped calls*?
Would churn for affected customers decrease by 0.8%?

When can *predictive analytics models* cross over into *prescriptive* analytics?

1. Has this action been **previously tried**?
2. Does the effect of this action on the outcome **pass the causality checklist**?
3. Does the predictive model **account for confounds**?
   (matching, regression with controls)

Predictive analytics
Anticipating Outcomes



Prescriptive analytics
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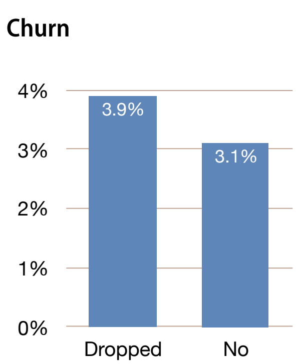

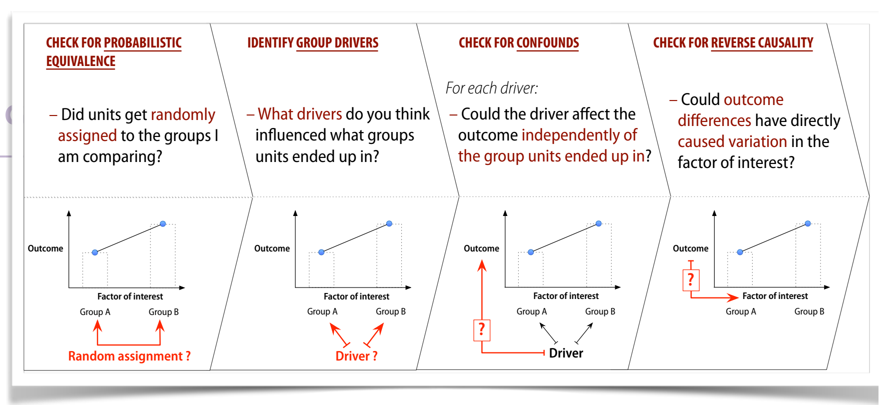

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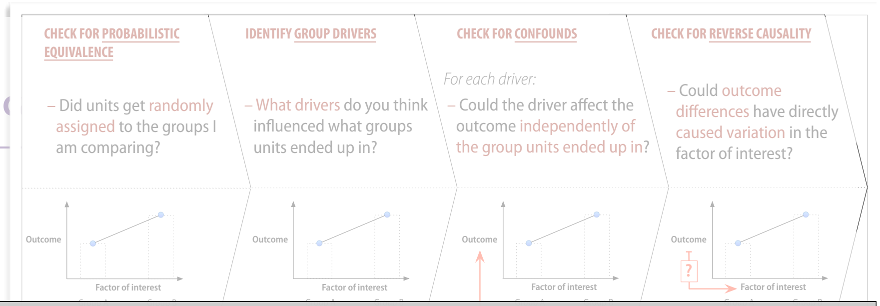

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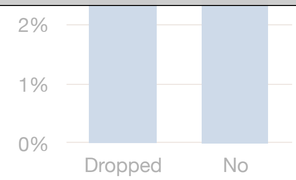


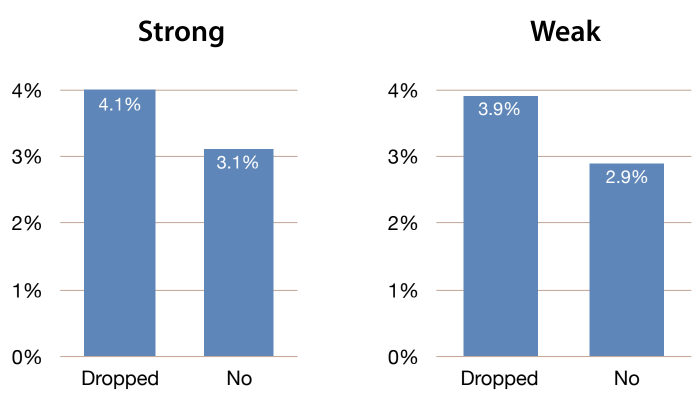
Explore the data and re-analyze it after controlling for the possible confound

- Areas with strong competition experience airwave congestions, leading to many dropped calls

Independently, competition makes consumers more likely to churn

Competition is possible **confound**

If you look at regions with weak vs. strong competition
and find this pattern, what do you conclude?



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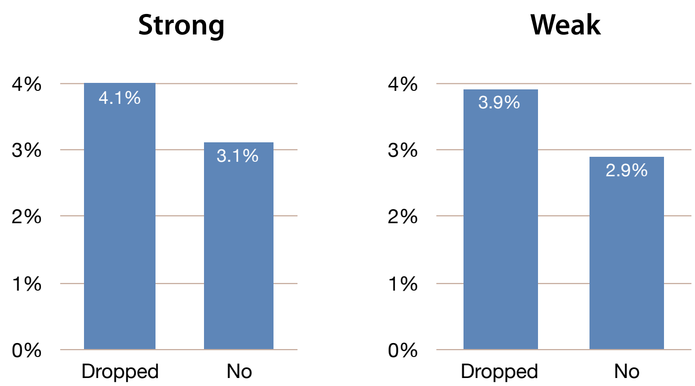

Dropped calls are more likely to be causal

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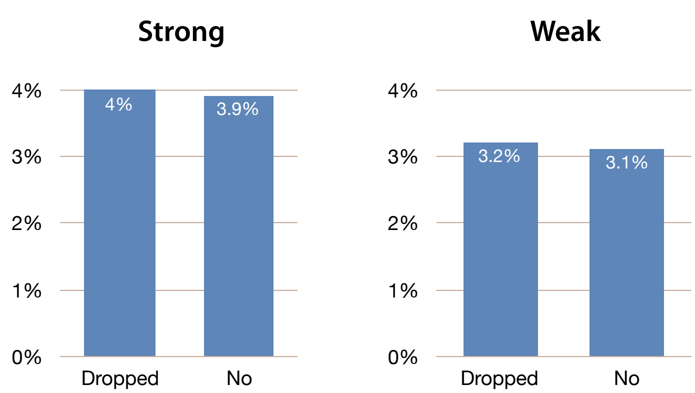

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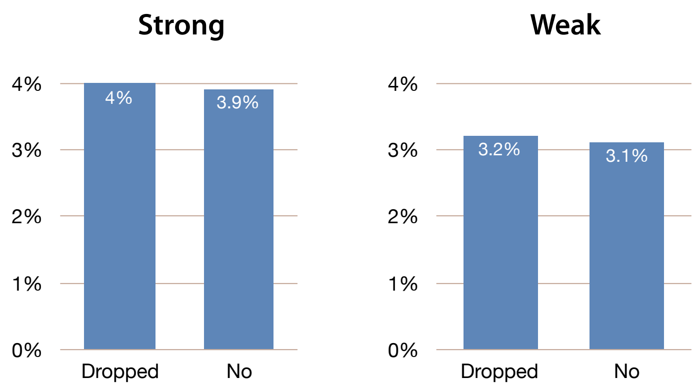

Dropped calls are not causal

To control for a potential confound, we need to include the potential confound in the predictive model

S-MOBILE VARIABLES

Description
Age in days of current equipment
Handset is new with subscription
Mean number of dropped voice calls
High credit rating - aa (as opposed to medium or low)
Prizm code is rural (as opposed to urban or suburban)
Occupation - clerical (as opposed to other occupations)
Number of calls previously made to retention team
Monthly overage minutes of use
Monthly minutes of use
Monthly revenue
% Change in minutes of use (1st to 2nd month)
% Change in revenues (1st to 2nd month)
Initial Signup In-Store
Monthly Visits to S-Mobile Web Site
Auto-Renewal
Family Plan: # of Associated S-Mobile Accounts

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Family Plan: # of Associated S-Mobile Accounts
Competition

If the effect of dropped calls persists, competition ***is not*** a confound;
if the effect goes away, competition ***is*** a confound

1. Has this action been previously tried?
2. Does the effect of this action on the outcome pass the causality checklist?
3. Does the predictive model account for confounds?
(matching, diff-in-diff, regression adjustment)

When can *predictive* analytics models cross over into *causal* analytics?

Predictive analytics:
Anticipating Outcomes

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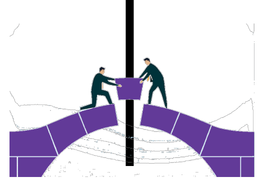
Causal analytics
Changing Outcomes



You must consider 3 things to bridge *predictive* and *causal* analytics

***Predictive* analytics:**
Anticipating Outcomes

***Causal* analytics**
Changing Outcomes

1. **Has this action been previously tried?**

no / yes

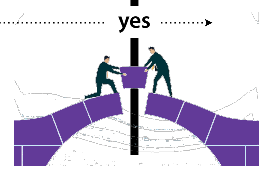
2. **Does the effect of this action on the outcome pass the causality checklist?**

no / yes → Model can predict based on *"what if"* variable values

3. **Does the predictive model account for confounds?**
   (matching, diff-in-diff, regression adjustment)

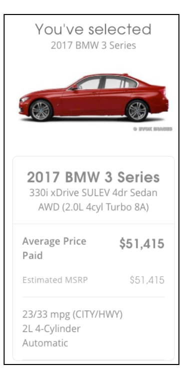
no / yes → Model can predict based on *"what if"* variable values

Model can only predict based on ***naturally-occurring*** variable values

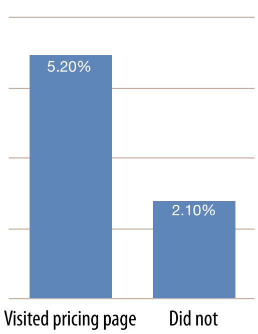


Edmunds.com uses web-site behavior to predict lead generation

edmunds.com

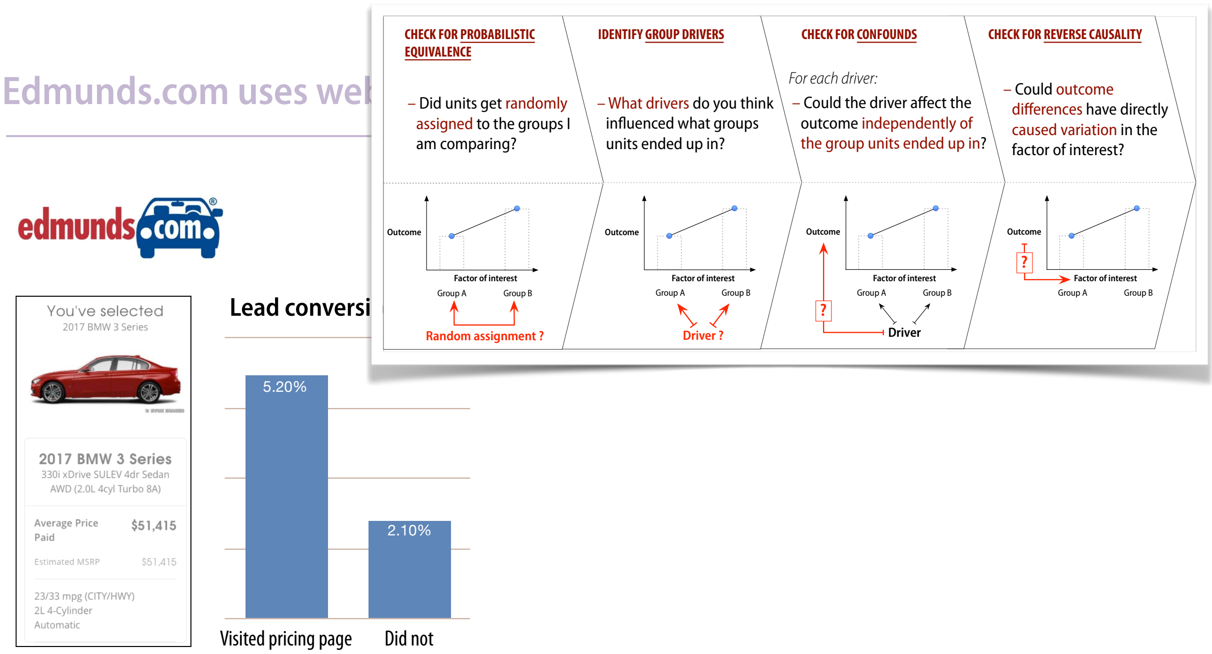


Lead conversion



STATEMENT OF FACT

If a consumers visits the pricing page he/she is more likely to submit a lead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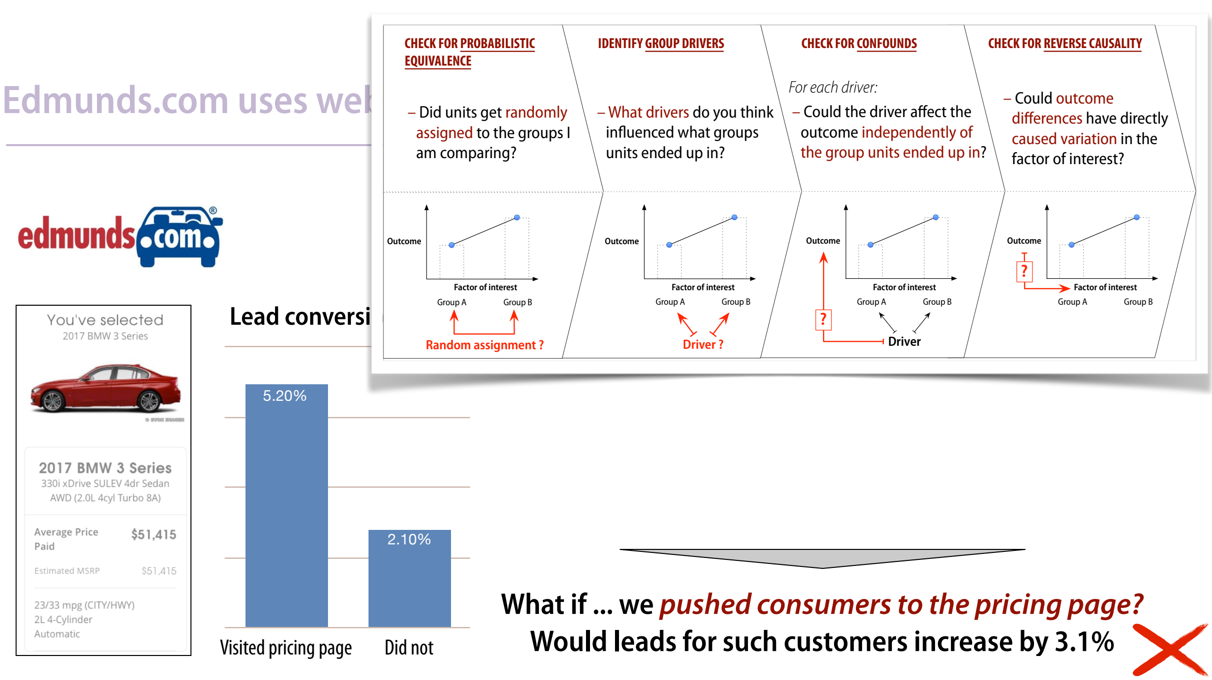
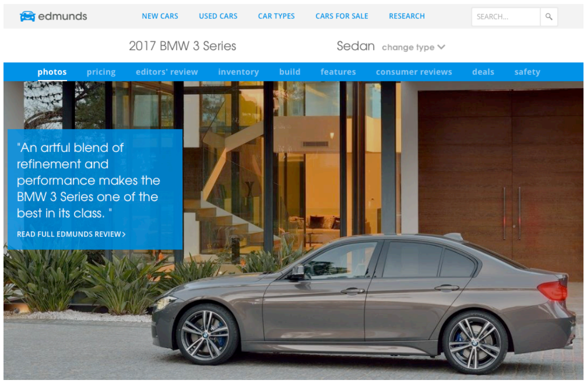
edmunds.com
You've selected
2017 BMW 3 Series
2017 BMW 3 Series
330i xDrive SULEV 4dr Sedan
AWD (2.0L 4cyl Turbo 8A)
Average Price Paid
$51,415
Estimated MSRP
$51,415
23/33 mpg (CITY/HWY)
2L 4-Cylinder
Automatic
Lead conversi
5.20%
2.10%
Visited pricing page
Did not
CHECK FOR PROBABILISTIC EQUIVALENCE
– Did units get randomly assigned to the groups I am comparing?
IDENTIFY GROUP DRIVERS
– What drivers do you think influenced what groups units ended up in?
CHECK FOR CONFOUNDS
For each driver:
– Could the driver affect the outcome independently of the group units ended up in?
CHECK FOR REVERSE CAUSALITY
– Could outcome differences have directly caused variation in the factor of interest?
Outcome
Factor of interest
Group A
Group B
Random assignment ?
Driver ?
?
Driver

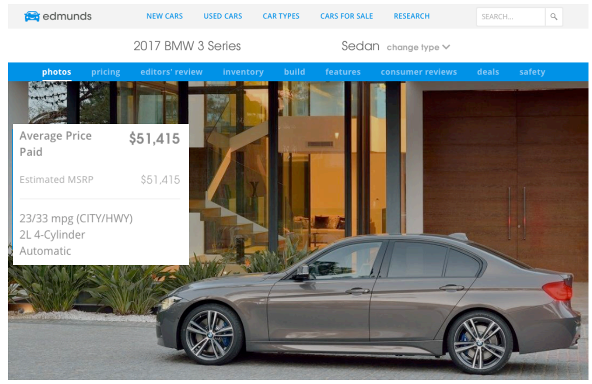

Edmunds.com uses wel
edmunds.com
You've selected
2017 BMW 3 Series
2017 BMW 3 Series
330i xDrive SULEV 4dr Sedan
AWD (2.0L 4cyl Turbo 8A)
Average Price Paid
$51,415
Estimated MSRP
$51,415
23/33 mpg (CITY/HWY)
2L 4-Cylinder
Automatic
Lead conversi
5.20%
2.10%
Visited pricing page
Did not
CHECK FOR PROBABILISTIC EQUIVALENCE
– Did units get randomly assigned to the groups I am comparing?
IDENTIFY GROUP DRIVERS
– What drivers do you think influenced what groups units ended up in?
CHECK FOR CONFOUNDS
For each driver:
– Could the driver affect the outcome independently of the group units ended up in?
CHECK FOR REVERSE CAUSALITY
– Could outcome differences have directly caused variation in the factor of interest?
Outcome
Factor of interest
Group A
Group B
Random assignment ?
Driver ?
?
Driver
What if ... we pushed consumers to the pricing page?
Would leads for such customers increase by 3.1%

Instead, suppose some consumers had randomly been exposed to pricing on the car's homepage

CONDITION A



CONDITION B



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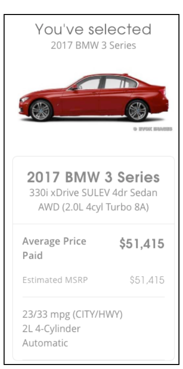
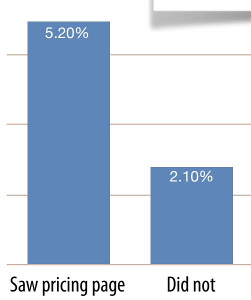
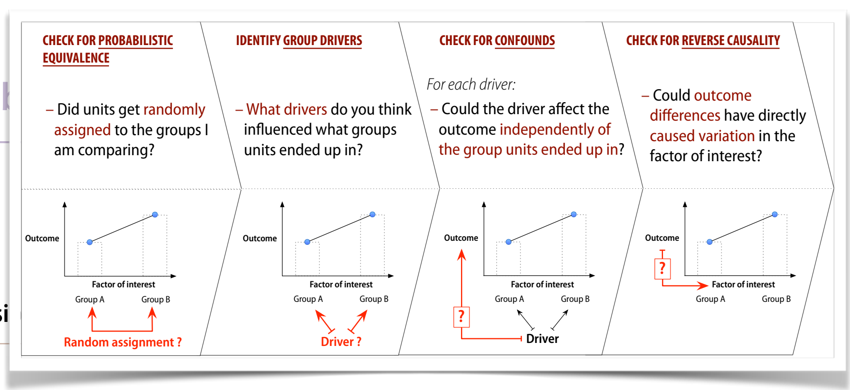


Lead conversi





Groups are **probabilistically equivalent** because of randomization

What if ... we *pushed consumers to see pricing?*
Would leads for such customers increase by 3.1%

You must consider 3 things to bridge *predictive* and *causal* analytics

***Predictive* analytics:**
Anticipating Outcomes

***Causal* analytics**
Changing Outcomes

1. **Has this action been previously tried?**

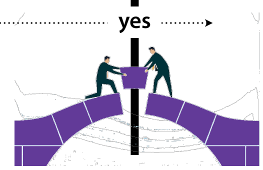
no · yes

2. **Does the effect of this action on the outcome pass the causality checklist?**

no · yes → Model can predict based on ***"what if"*** variable values

3. **Does the predictive model account for confounds?**
   (matching, diff-in-diff, regression adjustment)

no · yes → Model can predict based on ***"what if"*** variable values



Model can only predict based on ***naturally-occurring*** variable values

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Kellogg School of Management
Northwestern University

S-Mobile

S-Mobile:
Predicting Customer Churn

Shu Ying Seng was a member of the first graduating class of the new Master in Analytics program of the National University of Singapore (NUS). In contrast to many of her classmates who had little prior work experience, Shu Ying had worked for the last 7 years for S-Mobile, a leading cellphone carrier in Singapore. Because she had loved working there and S-Mobile had helped her pay for her degree, she had returned to the company half a year ago.

We identified variables related to customer churn

RESULTS FROM PREDICTIVE MODEL

Variable Type	Variable	Description	Dummy	z	p-value	Mean	Min	Max	OR Importance	+/–	Typical Difference
Customer action	retcalls	Number of calls previously made to retention team	0	9.5	0.000	0.04	0	4	**1.30**	+	0.2
Customer action	custcare	Mean number of customer care calls	0	-1.92	0.055	1.8	0	366	**1.07**	–	6.0
Customer characteristic	creditaa	High credit rating - aa (as opposed to medium or low)	1	-8.24	0.000	12%	0	1	**1.41**	–	0 to 1
Customer characteristic	occret	Occupation - retired (as opposed to other occupations)	1	-2.29	0.022	1.4%	0	1	**1.28**	–	0 to 1
Customer characteristic	occcrft	Occupation - crafts (as opposed to other occupations)	1	-2.37	0.018	3%	0	1	**1.20**	–	0 to 1
Customer characteristic	occprof	Occupation - professional (as opposed to other occupations)	1	-3.45	0.001	17%	0	1	**1.13**	–	0 to 1
Customer usage	months	# of months the customer has had service	0	-9.71	0.000	19	6	61	**1.45**	–	10
Customer usage	mou	Mean monthly minutes of use	0	-6.83	0.000	515	0	7668	**1.40**	–	525
Customer usage	phones	# Handsets Issued	0	5.49	0.000	1.8	1	20	**1.22**	+	1.3
Customer usage	overage	Mean monthly overage minutes of use	0	3.74	0.000	41	0	4321	**1.17**	+	100
Customer usage	roam	Mean number of roaming calls	0	3.69	0.000	1.2	0	692	**1.11**	+	7.3
Customer usage	uniqsubs	Number of individuals listed with the account	0	3.78	0.000	1.5	1	18	**1.10**	+	0.9
Customer usage	threeway	Mean number of threeway calls	0	-2.37	0.018	0.3	0	56	**1.08**	–	1.1
Equipment characteristic	eqpdays	Number of days of the current equipment	0	16.32	0.000	391	-5	1823	**1.87**	+	254
Equipment characteristic	refurb	Handset is refurbished (as opposed to new)	1	5.91	0.000	14%	0	1	**1.25**	+	0 to 1
Equipment characteristic	webcap	Hanset is web capable	1	-2.39	0.017	90%	0	1	**1.12**	–	0 to 1
Quality	unansvce	Mean number of unanswered voice calls	0	2.04	0.041	28	0	849	**1.08**	+	38
Quality	dropvce	Mean number of dropped voice calls	0	2.1	0.036	5.9	0	133	**1.07**	+	9
Quality	blckvce	Mean number of blocked voice calls	0	1.7	0.090	4.1	0	311	**1.04**	+	11
Usage trends	changem	% Change in minutes of use (over 4 month period)	0	-6.74	0.000	-16.3	-2868	5192	**1.28**	–	259
Usage trends	changer	% Change in revenues (over 4 month period)	0	6.09	0.000	-1.1	-571	2483	**1.24**	+	40

Next, we used *analytics-inspired creativity* to come up with churn management ideas

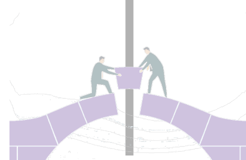
CHURN MANAGEMENT IDEAS

- **Reduce equipment age** by offering incentives to upgrade
- **Offer discounted service** to consumers with overages
- **Offer special acquisition programs** for high credit customers
- ...

But ... do these ideas reduce churn and if so, by how much?

Some of these ideas don't cross over into *prescriptive* analytics

Predictive analytics: *Anticipating Outcomes*	*Causal* analytics *Changing Outcomes*
1. Has this action been previously tried?	
3. Does the predictive model account for confounds? (matching, diff-in-diff, regression adjustment)	
Model can only predict based on *actual* individual-level variables	



Good results require a combination of *analytics*, *creativity*, and *managerial judgement*

Customer Analytics Course Structure

Customer Centric Marketing

- Customer Analytics and AI Overview (Class 1)
  AI and Analytics,
  Why Customer Analytics and AI 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