From Prediction to Action

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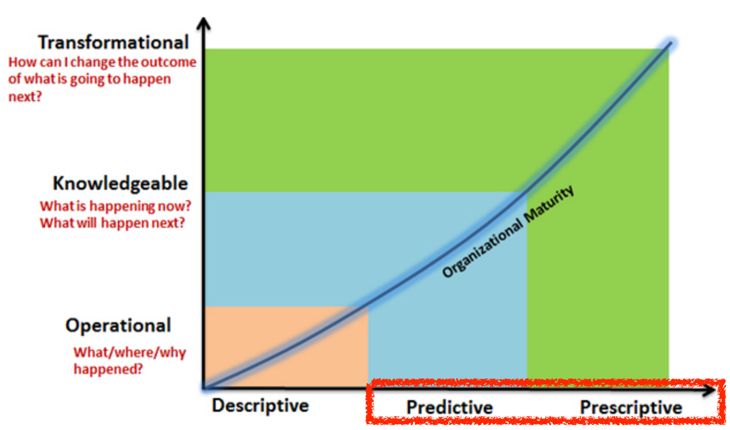
Customer Analytics

Predictive and prescriptive analytics are at the top of many "analytics maturity curves"

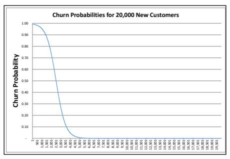


Source: bdisys.com

We used the *predictive analytics* churn model in the V-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 replace refurbished phones"
- "Lets give more referral bonuses"

Predict how the outcome would change if you implemented an action

"What is the likely effect on churn when replacing refurbished phones?"

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

One example, suppose we see high credit score customers are less likely to churn. We may focus acquisition on such customers in the future.

How to decide how much we may improve average churn rate if we increase such customers from 11% to 20%?

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;*

Another example, we see referred customers are less likely to churn. We may focus acquisition on referred customers in the future.

How to decide how much we may improve average churn rate if we increase referred customers from 11% to 20%?

What we did earlier:

```
## Predict the churn probability if we try to acquire more
## customers through referrals.

# First check the current churn rate of non-referred customers
# who are more likely to churn
non_referred_customers = vmobile[(vmobile['referred'] == 0) &
                                 (test_pred > 0.0194)]
print("Current churn rate of non-referred high churn customers:")
print(non_referred_customers['churn'].mean().round(4))

# Predict the churn probability for these customers
# if we give them a new phone

# Create a new dataframe with the selected features and the new subscription plan
new_data = non_referred_customers.copy()
new_data['referred'] = 1

# Predict the churn probability for the new data
new_pred = model.predict(new_data)

# Print the predicted churn probability
print("Predicted churn probability for the new referral:")
print(new_pred.mean().round(4))
```

```
Current churn rate of non-referred high churn customers:
0.0336
Predicted churn probability for the new referral:
0.0128
```

What we could have done more accurately!

```
## Non-referred customers who are more likely to churn
print("Current churn rate of non-referred high churn customers:")
print(non_referred_customers['churn'].mean().round(4))

## Calibrate churn rates of referred customers from data directly
referred_customers = vmobile[vmobile['referred'] == 1]
print("Churn rate of OBSERVED referred customers:")
print(referred_customers['churn'].mean().round(4))
```

```
Current churn rate of non-referred high churn customers:
0.0336
Churn rate of OBSERVED referred customers:
0.0092
```

- **The key is that we do observed these referred customers' <u>actual churn rate,</u> which makes the prediction approach redundant.**

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

("what if")

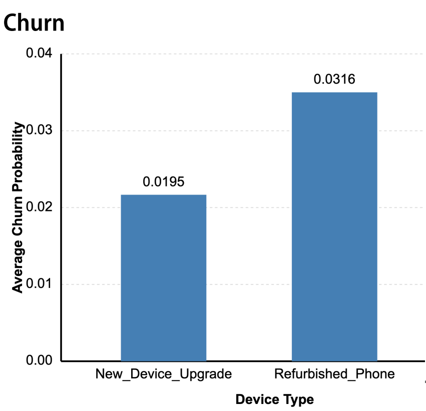
Predictions based on ***counterfactual*** individual-level variables, ***<u>do</u>*** require a ***causal relationship*** between these variables and the outcome for the prediction to be ***valid***

Consider the “new device” initiative

```
## Predict the churn probability if we give new phones to customers who have
## a refurbished phone and have higher churn rate than the average (1.94%).

# First check the current churn rate of these customers
refurb_customers = vmobile[(vmobile['newphone'] == 0) &
                          (test_pred > 0.0194)]
print("Current churn rate of customers with refurbished phone and high churn rates:")
print(refurb_customers['churn'].mean().round(4))

# Predict the churn probability for these customers
# if we give them a new phone

# Create a new dataframe with the selected features and the new subscription plan
new_data = refurb_customers.copy()
new_data['newphone'] = 1

# Predict the churn probability for the new data
new_pred = model.predict(new_data)

# Print the predicted churn probability
print("Predicted churn probability for the new phone:")
print(new_pred.mean().round(4))
```

```
Current churn rate of customers with refurbished phone and high churn rates:
0.0316
Predicted churn probability for the new phone:
0.0195
```


In V-Mobile assignment, phone age predicts churn probabilities



What we observed:

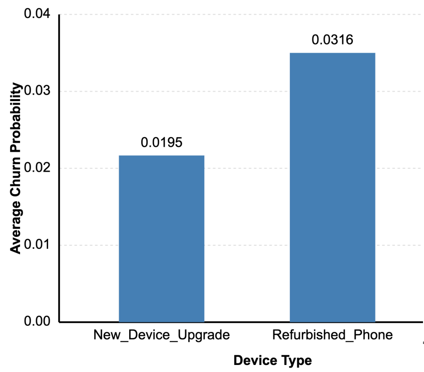
If a consumer has a newer phone, they are less likely to churn

- **Consumers churn because old phones result in bad experiences.**
- **Consumers churn because of low usage (hence old phone).**

What if ... *we offer subsidy for new phones (something did not actually happen)*?
Would churn for affected customers decrease to 0.0195%?

In V-Mobile assignment, phone age predicts churn probabilities

Churn



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Old phones are causal

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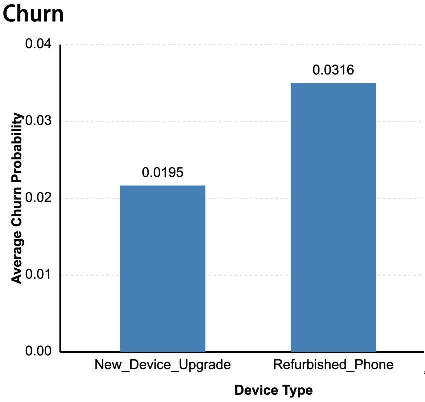
Churn



What we observed:

If a consumer has a newer phone, they are less likely to churn

- **Consumers churn because old phones result in bad experiences.**
- **Consumers churn because of low usage (hence old phone).**

Old phones are not causal

What if ... *we offer subsidy for new phones (something did not actually happen)*?
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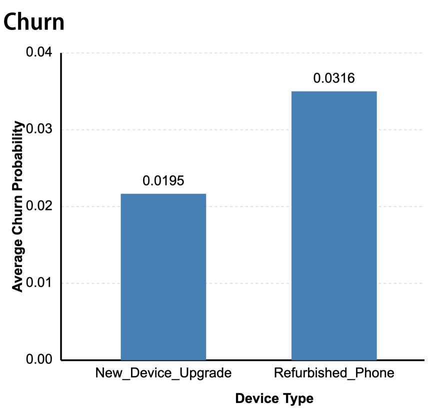

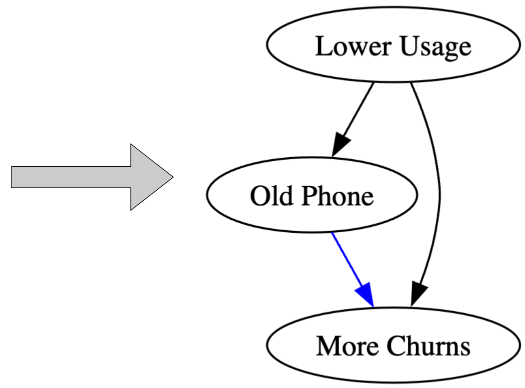

Predictive **analytics: What will happen? Predictors vary *<u>happen organically.</u>* And the relationship between the outcome and predictors is stable. Consequently, we can "predict" (in fact, more of describing data)**

Examples: Who is more likely to churn (low usage, old equipment, …)

Prescriptive **analytics: What should be done? Firms *<u>proactively change predictor</u>* levels, which may change who the customer is or how the person behaves. Consequently, the "prediction" may be incorrect**

Examples: Will the churn reduces if we take an action (subsidizing new phone, …)

We used the predictive analytics model in different ways

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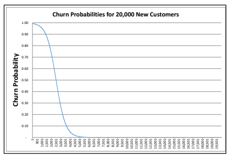


"Identify consumers with high churn probabilities"

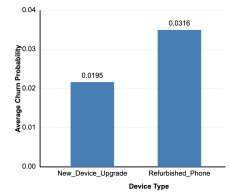
Use churn drivers to generate ideas to improve the outcome

- "Lets try to increase more usage"
- "Lets increase referred customers"
- "Lets offer incentives to keep phones up-to-date"

Causation is irrelevant

***Predictive* analytics**
Anticipating Outcomes

Predict how the outcome would change if you implemented an action



"What is the effect size of new phones on churn? And subsequently how much shall we subsidize?"

Causation is key

***Prescriptive* analytics**
Changing Outcomes

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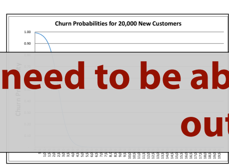

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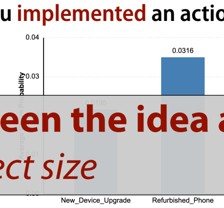


You need to be able prove a *causal relationship* between the idea and the outcome and estimate the *causal effect size*

"Identify consumers with high churn probabilities"

"What is the effect size of new phones on churn? And subsequently how much shall we subsidize?"

Causation is irrelevant

Causation is key

***Predictive* analytics**
Anticipating Outcomes

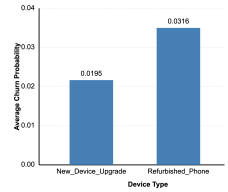
***Prescriptive* analytics**
Changing Outcomes

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

1. **Has this action been previously tried?**
   Directly use historical data and outcomes

2. **Can we apply a predictive model that accounts for common drivers or confounds?**
   (control the confounds, matching, diff-in-diff, etc.)

Predict how the outcome would change if you implemented an action



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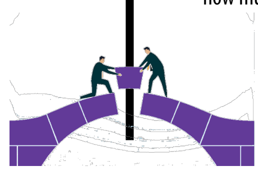

Causation is key

***Prescriptive* analytics**

Changing Outcomes