How Predictions Help

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Northwestern | Kellogg

CONSIDER AN OWNER OF A HIGH-END RESTAURANT TRYING TO “RIGHT-SIZE” SALMON ORDERING

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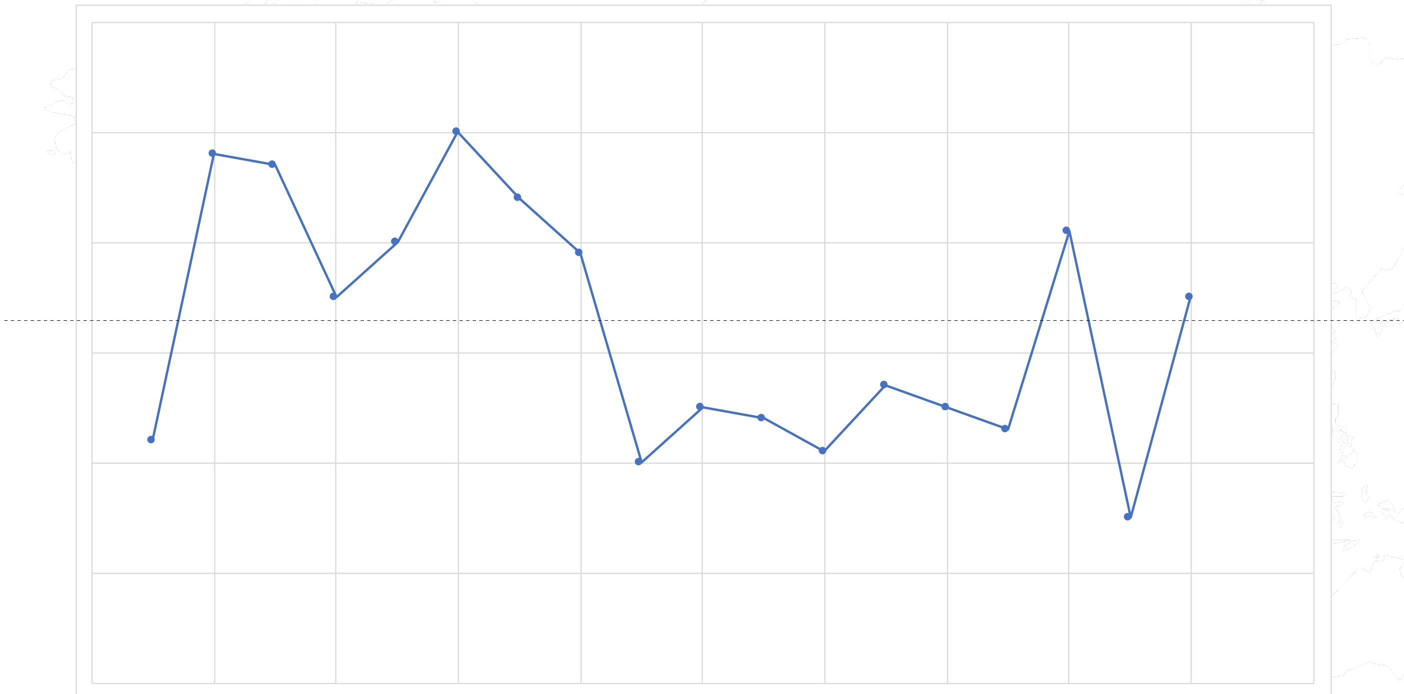
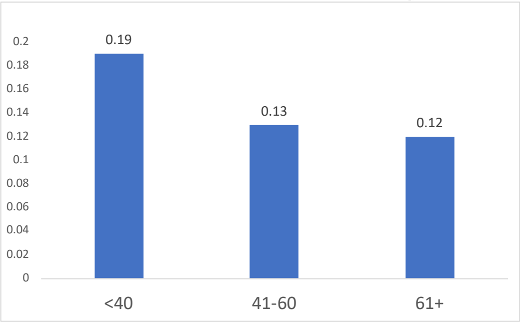
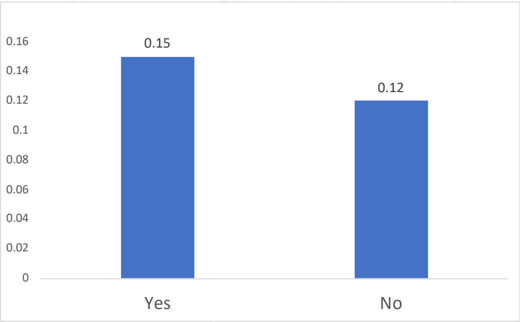


LOOKING BACKWARDS IS INFORMATIVE…

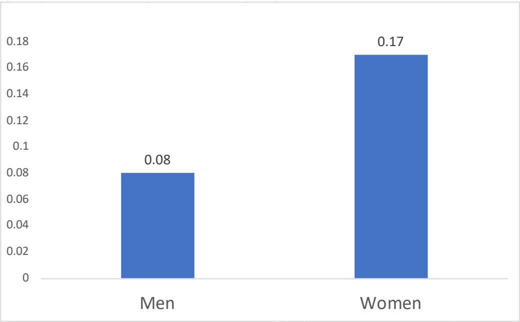
MORE SALMON FOR



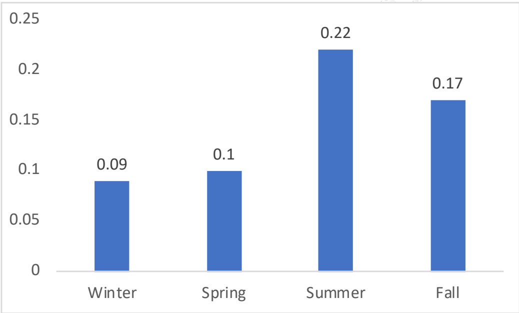
Younger guests



Chicago-area residents



Women



Warm weather

LOOKING BACKWARDS IS INFORMATIVE…

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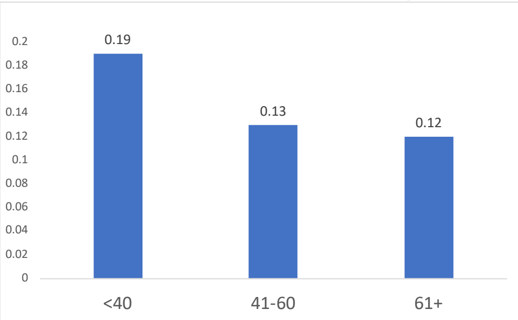
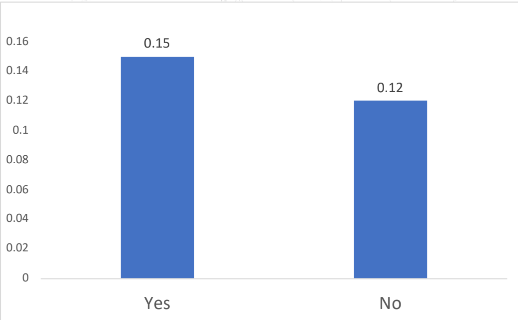


Younger guests



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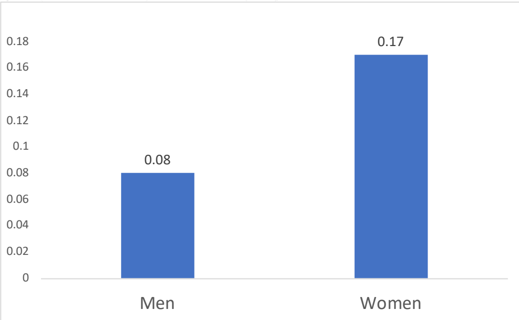
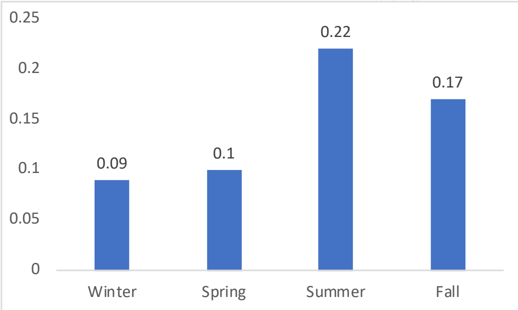


Women



Warm weather

How much salmon for upcoming
East Coast
CIO RoundTable
Winter Retreat

How much salmon for upcoming
Young Women's Business Association
Chicago Chapter

ALL PREDICTIONS WORK LIKE THIS

PAST

Identify trends from "historical" data

FUTURE

Infer those trends will remain the same for future

PREDICTION IS AT THE INDIVIDUAL LEVEL

THE PAST

Age	Chicago	Gender	Salmon?
35	Yes	Female	Yes
64	No	Male	No
39	No	Female	No
76	Yes	Female	No
55	Yes	Male	Yes
56	No	Male	No
49	Yes	Female	No
38	Yes	Male	Yes
52	No	Male	No
…	….	…	…

THE FUTURE

Age	Chicago	Gender	Res Date	Salmon?
46	No	Male	Sat. night	?
75	No	Female	Sat. night	?
50	Yes	Female	Sat. night	?
64	Yes	Female	Sat. night	?
64	Yes	Male	Sat. night	?
74	No	Male	Sat. night	?
46	Yes	Female	Sat. night	?
66	Yes	Female	Sat. night	?
…	….	…	…	…

Predictive Tool

p(salmon) = .086
p(salmon) = .172
p(salmon) = .003

Sum up for all 100 guests = 15.1 orders of salmon

WHY IS PREDICTION HELPFUL?

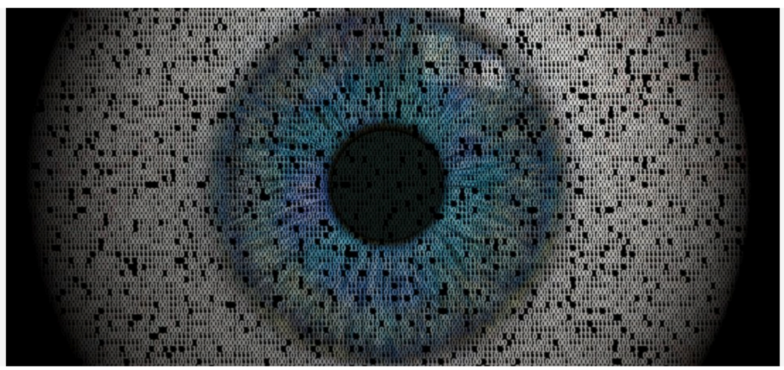
LEAD

IBM Says It Now Has a Patent on a 'Secret' Way to Predict When Employees Will Quit, and It's 95 Percent Accurate. (Is This Brilliant or Terrifying?)

You don't want to be surprised--but does anyone want their life predicted like this?

in f

By Bill Murphy Jr. www.billmurphyjr.com @BillMurphyJr



PREDICTIONS HELP MANAGERIAL DECISION MAKING IN 4 WAYS

PLANNING: accepting what will happen, but making sure you're ready for it
SELECTING: creating a group based on those with most desirable outcomes
TARGETING: intervening with selected individuals to try to change what will happen
IDEATING: finding levers to pull to cause good outcomes

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First, let's walk through what a prediction looks like, so we can see how it informs each.

EXAMPLE: A HIGH-END HOTEL'S PREDICTIVE CHURN MODEL

- 32 hotels worldwide
- Average of 90 rooms per hotel
- 36% customer churn, defined as: *no stay within 6 months of last stay*

PREDICTIVE MODEL BEGINS WITH DATA

HotelChurn

Joel

Table | Stats

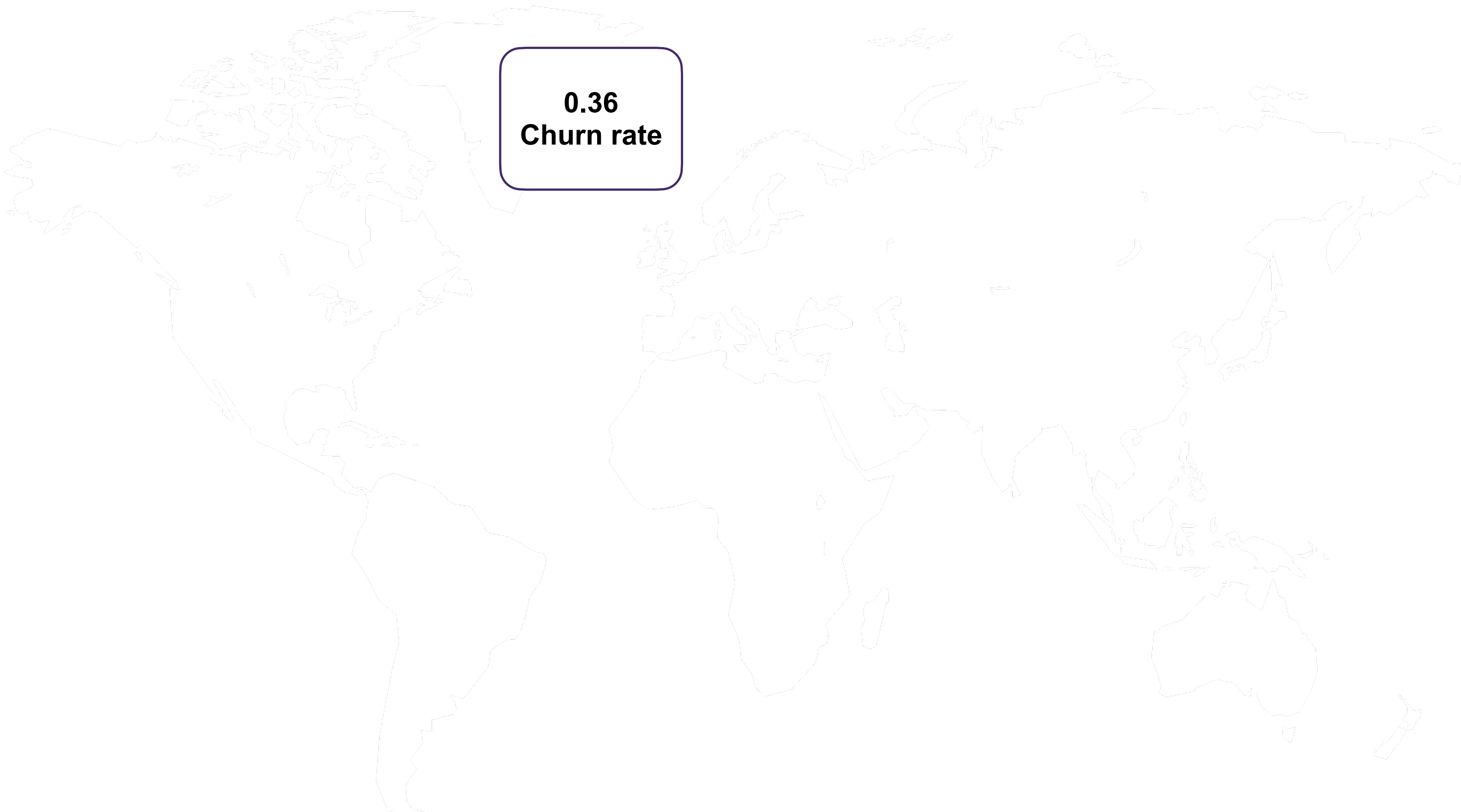
17 / 38 rows < 1 of 3 >

custid	rebook6mos	roomserv	shuttle	fitness	restaurant	check-in	specreq	age	gender	purpose	homecountry
556,287	1	0	1	0	1	in-person	0	31.3	male	leisure	us
222,794	1	0	0	0	4	kiosk	0	50.1	female	leisure	brazil
832,099	0	0	0	0	3	app	0	76.4	male	leisure	spain
616,626	1	1	1	0	7	in-person	0	50.7	male	work	us
219,131	1	0	1	0	4	kiosk	1	39.1	female	work	australia
416,877	0	0	0	0	4	app	1	63.4	male	leisure	china
802,106	1	0	1	0	1	in-person	0	58	female	leisure	us
887,655	0	0	1	0	4	kiosk	0	28.1	male	work	us
529,202	1	0	1	0	0	in-person	0	79.9	male	work	china
537,305	1	1	1	1	3	in-person	0	21	female	work	spain
983,077	0	1	1	1	5	app	0	45.3	female	work	brazil
829,753	1	0	1	1	0	in-person	0	44.7	male	leisure	china
170,204	1	1	1	1	0	in-person	0	34.7	male	leisure	us
561,390	0	0	0	1	6	app	1	71.2	female	work	japan
632,289	1	0	0	1	3	kiosk	1	71.5	male	leisure	brazil
561,612	1	1	0	0	0	in-person	0	43.9	male	leisure	spain
348,779	0	1	0	1	0	in-person	0	70.2	female	work	us

Outcome

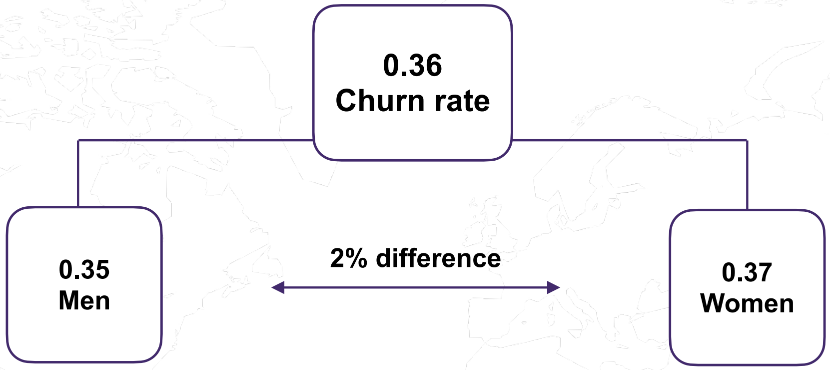
Inputs / Predictors

CHURN DECISION TREE



0.36
Churn rate

CHURN DECISION TREE



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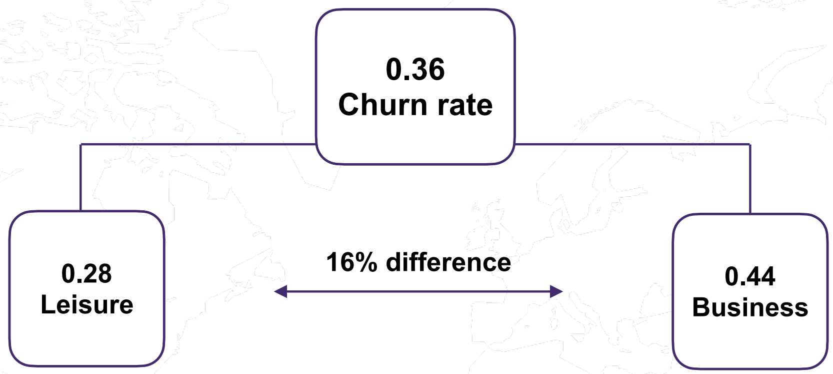

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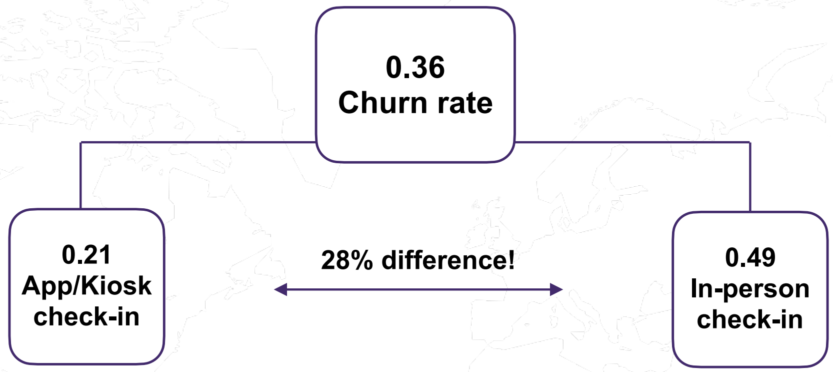

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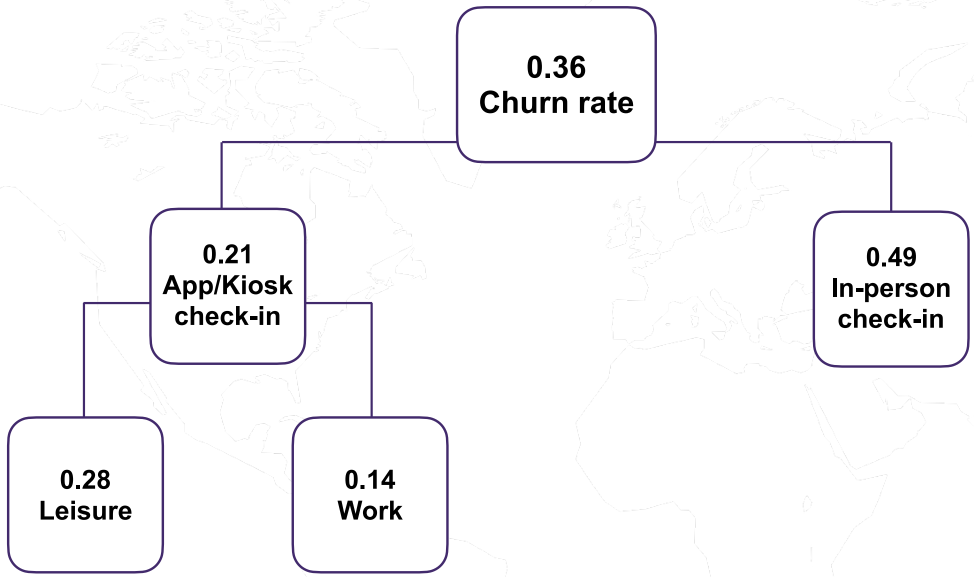

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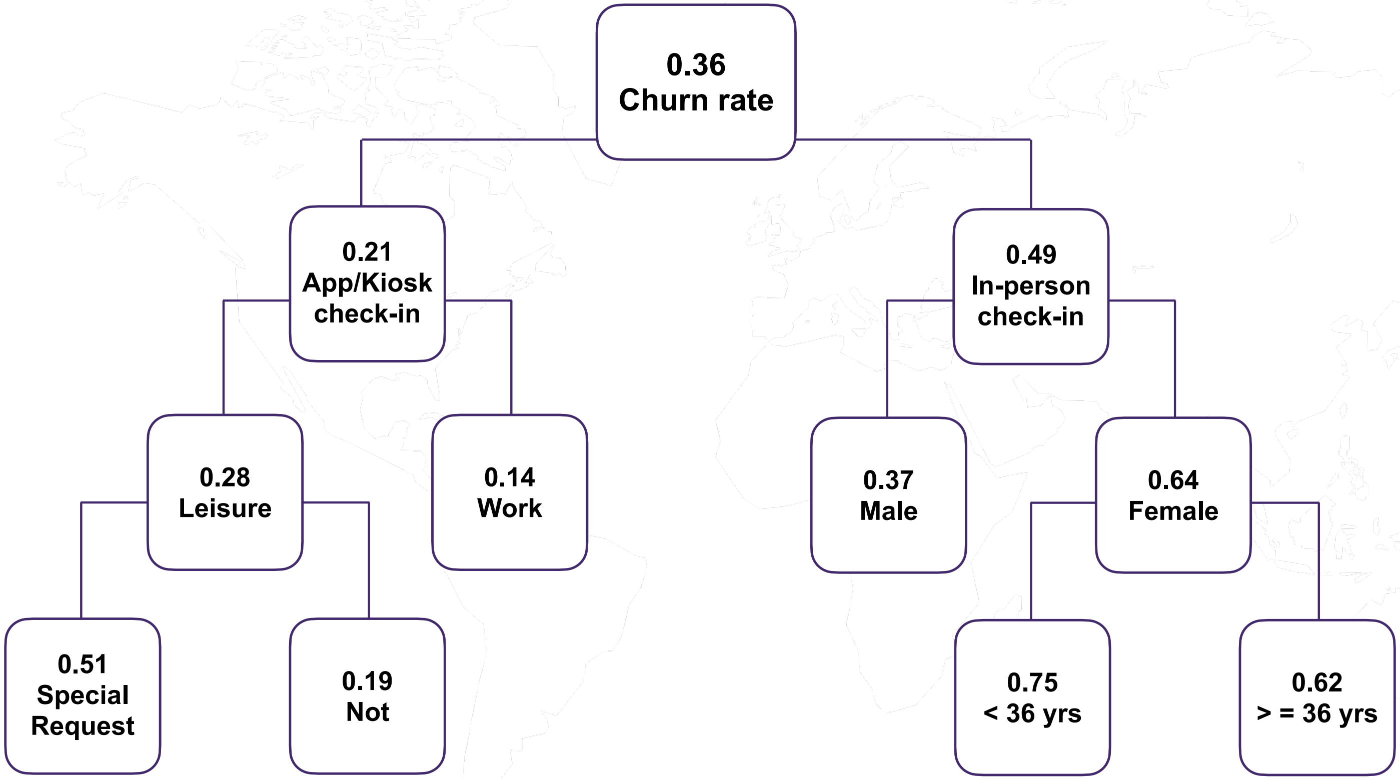

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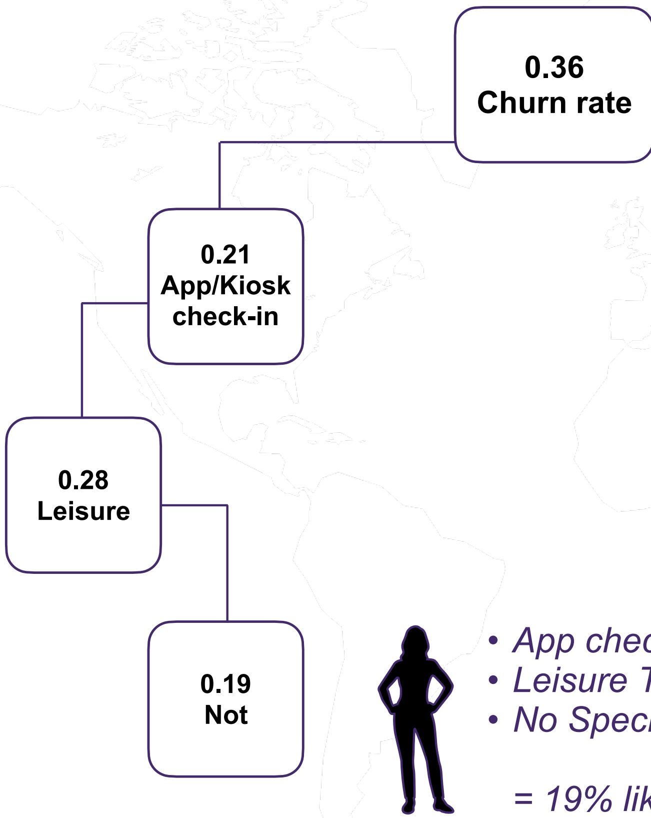


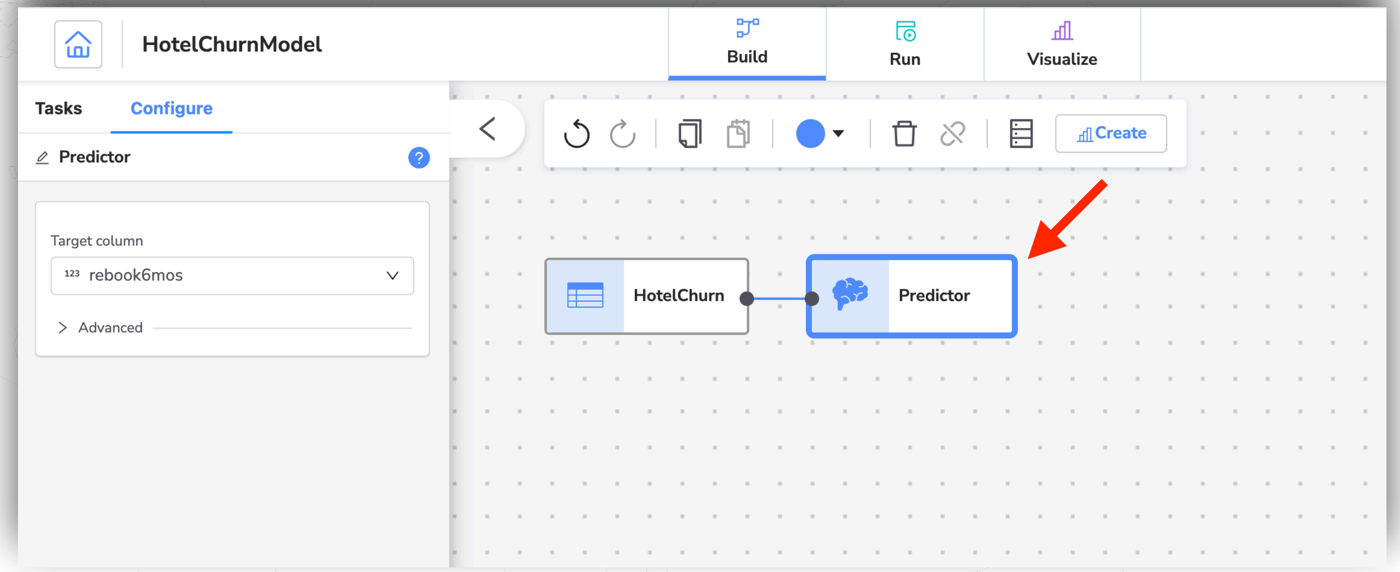
- *App check-in*
- *Leisure Travel*
- *No Special Request*

= 19% likely to churn

THERE ARE MANY KINDS OF PREDICTIVE TOOLS

To find the most accurate model, you could just keep trying different algorithms…

But today's consumer-facing tech tools can automatically find the best model for you!



— 100% +

10 / 38 rows < 1 of 4 >

sed on up to 10,000 sampled rows

req	age	gender	purpose	homecountry	Probability	
0	31.3	male	leisure	us	0.927 314 937 ...	Explain
0	50.1	female	leisure	brazil	0.813 864 648 ...	Explain
0	76.4	male	leisure	spain	0.746 664 524 ...	Explain
0	50.7	male	work	us	0.661 574 542 ...	Explain
1	39.1	female	work	australia	0.537 610 173 ...	Explain
1	63.4	male	leisure	china	0.888 415 396 ...	Explain
0	58	female	leisure	us	0.920 725 822 ...	Explain
0	28.1	male	work	us	0.745 765 864 ...	Explain
0	79.9	male	work	china	0.591 027 259 ...	Explain
0	21	female	work	spain	0.978 200 495 ...	Explain

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PREDICTION USE #1
PLANNING: BEING READY FOR WHAT WILL HAPPEN

Which customers are likely to upgrade?

customer	p(upgrade)
1	0.38
2	0.11
3	0.99
4	0.41
…	…
999	0.28
1000	0.18
TOTAL	**172.88**

PREDICTION USE #1
PLANNING: BEING READY FOR WHAT WILL HAPPEN

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FORECASTING

- Improved Sales / Revenue Forecasting
- Accurate Customer Support Needs
- **Grocery Store Demand Planning**

PRECTION USE #2

SELECTING: OPTIMAL GROUP COMPOSITION

PREDICTION USE #2
SELECTING: OPTIMAL GROUP COMPOSITION

LINKING PREDICTIVE MODELS TO BUSINESS DECISIONS

Data Scientists Care About
Confusion Matrix

Actual \ Predicted	-	+
-	**TN**	**FP**
+	**FN**	**TP**

Data Science

Business Leaders Care About
Payoff Matrix

Actual \ Predicted	-	+
-	**$Benefit**	**$Cost**
+	**$Cost**	**$Benefit**

Business Decisions

PREDICTION USE #3
TARGETING: SPECIFIC INITIATIVES FOR SPECIFIC INDIVIDUALS

Which customers are likely to upgrade?

customer	p(upgrade)
1	0.38
2	0.11
3	0.99
4	0.41
…	…
999	0.28
1000	0.18
TOTAL	**172.88**

Can selectively deploy initiatives to try to change behavior

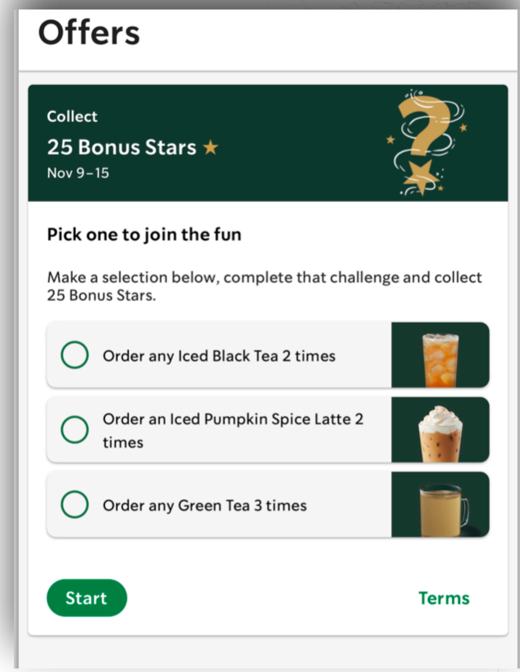
- Customized offers to incentivize purchase / upgrade
- Targeted intervention

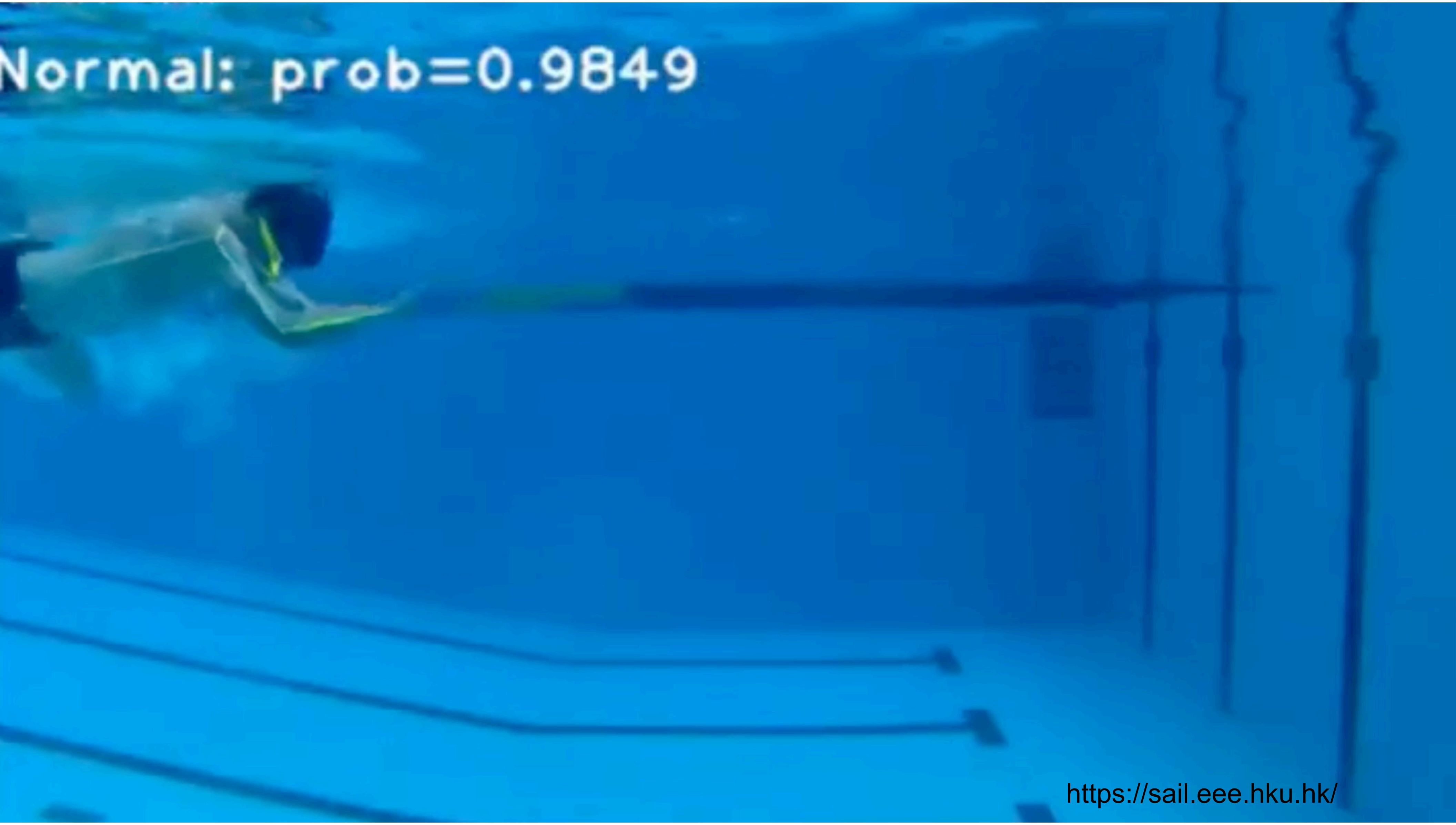
PREDICTION USE #3
TARGETING: SPECIFIC INITIATIVES FOR SPECIFIC INDIVIDUALS

TARGETING is one of the keys to "customizing" managerial decision-making.

It allows us to selectively deploy our resources to selected individuals.

PREDICTION USE #3
TARGETING: SPECIFIC INITIATIVES FOR SPECIFIC INDIVIDUALS





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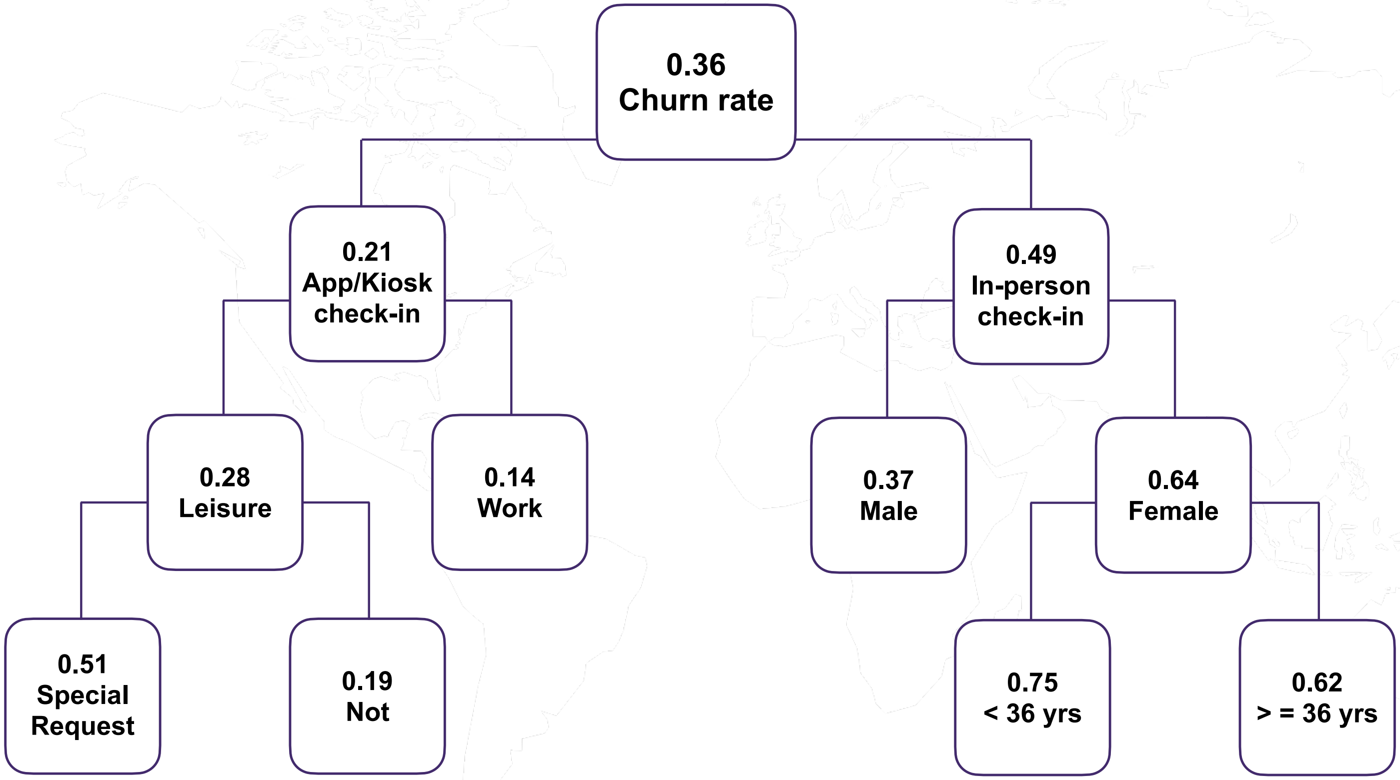
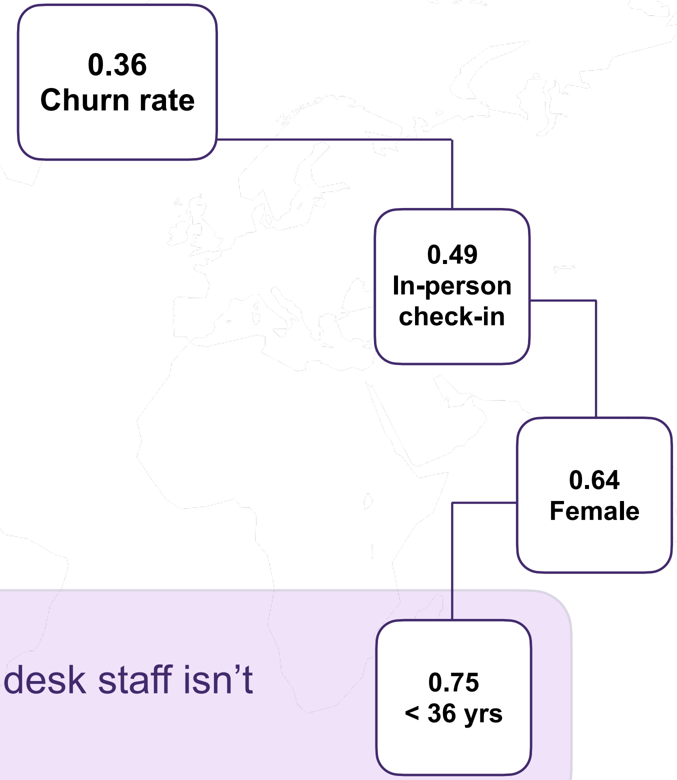
PREDICTION USE #4
IDEATING: GENERATING IDEAS TO CAUSE GOOD OUTCOMES



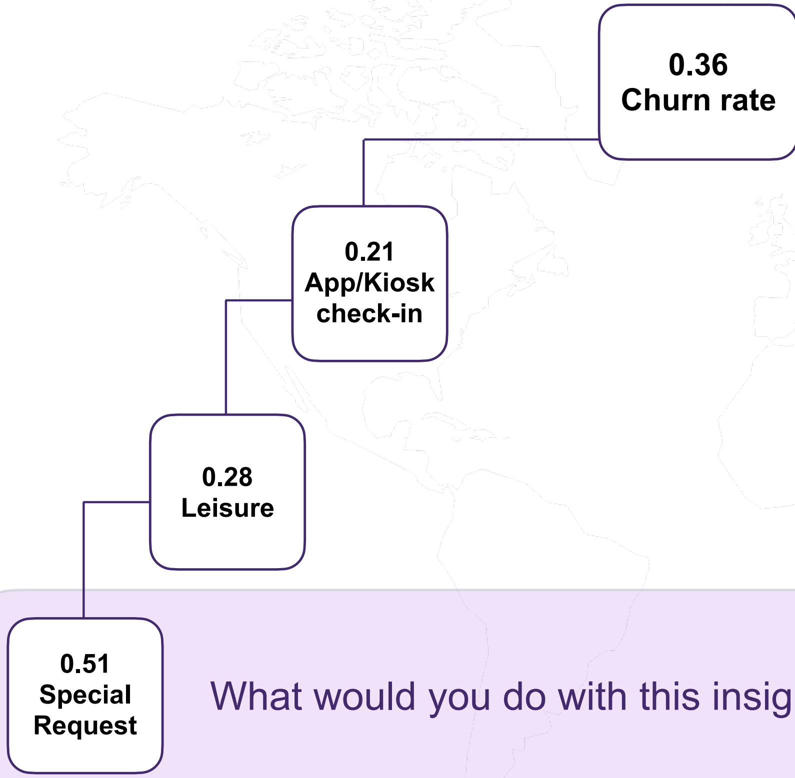
PREDICTION USE #4
IDEATING: GENERATING IDEAS TO CAUSE GOOD OUTCOMES



Maybe: front desk staff isn't trained well

Solution = Better Training?

PREDICTION USE #4
IDEATING: GENERATING IDEAS TO CAUSE GOOD OUTCOMES



What would you do with this insight?

PREDICTION USE #4
IDEATING: GENERATING IDEAS TO CAUSE GOOD OUTCOMES

0.36
Churn rate

0.21
App/Kiosk check-in

0.28
Leisure

0.51
Special Request

IDEATION is powerful, but need to be careful!!

Maybe: tech-savvy leisure travelers are demanding, and hotel isn't great at fulfilling special requests

Or maybe: tech-savvy leisure travelers who put in special requests are comparison shoppers and very price sensitive

Solution =

Improve special request workflow

Assess pricing strategy

PREDICTION USE #4
IDEATING: GENERATING IDEAS TO CAUSE GOOD OUTCOMES

ML / AI	EXPLORE	SOLVE	TEST
Where should I focus my efforts?	Why does the problem exist?	How can I change the outcome?	Does the solution work?