UBER Case Study

All products developed at UBER have algorithm (mathematical/statistical) behind built by tactical data scientists mostly holding doctoral degrees in data science field. Data science is present as a function in every product developed at UBER using high end analytics and data science tools and techniques as it is a highly mature technical company. Role of data science in innovation at Uber is to provide useful insights on market needs that enable uber to put & run different experiments to satisfy and improve customer's needs.

Data Science team is active and adapts to data/ feedback generated by riders/ drivers and implements relevant changes to product. No product stays for more than 18 months (about 1 and a half years) at UBER, this shows they favor releasing products early and take advantage and later keep on improving product in which data scientists play key role.

Due to this mindset, the team produced ideas of UBER pool, express, eats, health, and Autonomous car serving separate set of customers who need food delivered, need to reach healthcare facility or to think on future course of mobility and being environmentally friendly.

Data science is key for Uber in terms of decision-making and guiding their innovation in new products. We can tell that by the percentage of data scientists working at the company (2.4% according to supporting data) and specific policies. The moratorium on any changes in treatment and control experiments shows UBER is concerned about the quality and validity of its data and speaks to a culture of understanding both the importance of data science and what it takes to empower data science teams.

Also, the case mentions that every new product introduced has rigorous testing and data analysis before, during and after implementation.

Uber runs different tests to cover the weaknesses of each specific kind of test. For example, when introducing Express, Uber ran simulations using historical and live data to test and perfect their algorithm. These simulations could not consider user feelings and sensitivity towards wait times and prices. Since the product was not available to compensate, Uber distributes conjoint surveys to customers to collect primary data.

Uber runs several types of experiments to improve its platform and products:

- **User level A/B:** Standard, user-level A/B experiments used to compare and understand the effects of changes and decisions made to the platform on user behavior.

Cons: Cannot test new products since A/B experiments are focused on user level. Not scalable considering Uber's size of operations since each demographic group needs its own set of tests.
Pros: Allows Uber to compare the effect of changes in their UI/UX or platform. Easy to set up and can test more than 2 changes. Minimal contamination effect: will not interfere much with product-level data.

- **Switchbacks**: design used to evaluate effects of product tweak on some outcome variable of interest. Involves splitting each day of the week into an odd number of treatments and controlling set of hours to test effects of product tweak. Usually run over two weeks.

Cons: Experiment designed around finding aggregate effect of product changes over time, less focused towards analyzing day-level effects. Cannot test more than one change. Prone to contamination so you cannot run more than one per city. Targets one outcome variable.
Pros: allows Uber to quickly evaluate effects of product changes. Easy to set up.

- **Synthetic control experiments: create** control and treatment cities to simulate controlled experiments to study the effects of a product tweak on a set of outcome variables of interest.

Cons: synthetic controls require any changes to be significant – more than 5% - to be detectable, but the experiments usually create many less significant changes. More costly to set up, require blocking any other major changes in all cities involved.
Pros: allow Uber to get exact and valid results for product changes and their effect on more than one outcome variable.

Why does UBER Express since UBER Pool (2014) exist as a ride sharing service?

- Ridesharing may be the future of ride-hailing companies and should be innovated regularly
- To make ride sharing efficient, eco-friendly, and profitable as it was making loss
- Reduce loops/detours and improve match efficiency which leads to good ratings of rider and drivers

Solutions/Uniqueness with Express:

- Make riders wait and walk to the nearest pre-defined corners for pickups which will lead to fewer detours.
- Increase match efficiency (better rated drivers for riders and vice versa), decrease costs per ride
- More seat utilizations and more time for algorithms to optimize the route
- Express algorithm was built with a wait of two and five minutes

Few Concerns:

- It might be unsafe for riders to walk to pick up points (some routes might not be safe)
- Weather and emergency cases will not be applicable under UBER Express
- Not suitable for people with disabilities and Express limits privacy
- Real connection between drivers and Uber is missing which might lead to trust issues

1- <u>What is the effect of extending wait times from two to five minutes on the total number of shared rides completed</u>?
   Define total number of shared rides completed as trips_pool + trips_express.
   Use a linear regression with an interactive term between treatment and commute to find the effect of extending wait times from two to five minutes.

Effect of Treatment on Total Shared Rides

	Dependent variable:		
	total_shared	trips_pool	trips_express
	(1)	(2)	(3)
treat	50.8	123.7***	-73.0**
commute	-246.2**	-158.2	-88.0
total_matches	0.4***	-0.3***	0.7***
total_double_matches	0.1	-0.1*	0.2***
total_driver_payout	0.1***	0.05***	0.004
rider_cancellations	3.4***	2.4***	0.9*
treatTRUE:commute	-242.0**	-143.3	-98.7
Constant	822.1***	479.0***	343.1***
Observations	126	126	126
R^2	0.9	0.5	0.9
Adjusted R^2	0.9	0.5	0.9
Residual Std. Error (df = 118)	186.6	179.3	126.5
F Statistic (df = 7; 118)	151.9***	20.1***	259.5***
Note:	*p<0.1; **p<0.05; ***p<0.01		

Outside of rush hours, increasing wait time from 2 to 5 minutes does not have a significant effect on the total number of shared ride trips. Within rush hours, however, there is a significant effect: increasing wait time decreases the number of shared rides by 242 on average. This is consistent with the decrease in the number of shared rides caused solely by rush hours (-246), so we can attribute the decreased number of shared rides to the effect of rush hours with some certainty.

Taking a closer look at the effect of treatment on each type of shared ride product reveals an interesting aside. Regression (2) in the graph shows the effect of same variables on the total number of UberPOOL trips. Increasing wait time outside of rush hours increases the number of POOL trips. There is no significant effect during rush hours. Regression (3) shows the effect of same variables on the total number of POOL Express trips. Increasing wait time outside of rush hours decreases the number of Express trips. There is no significant effect within rush hours.

From this we can conclude that increasing wait time outside of rush hours makes riders substitute away Express and towards POOL. They are still willing to use a shared ride product but would prefer to pay more to avoid having to wait more.

2- <u>What is the effect of extending wait times from two to five minutes on the proportion of shared rides that were matched</u>?

Define proportion of shared rides that were matched as total_matches / total_shared, since each double match must be a match.

Use a linear regression with interactive term for commute and treatment.
Formula:

$$Proportion\ of\ Matched\ Shared\ Rides = \beta_0 + \beta_1 * Treatment_i + \beta_2 * Commute_i + \beta_3 * Treatment_i * Commute_i + \beta_4 * Total\ Driver\ Payout + \beta_5 * Rider\ Cancellations$$

Proportion of Matched Shared Rides=β0+ β1 * Treatmenti+ β2*Commutei+ β3*Treatmenti*Commutei+ β4*Total Driver Payout+ β5*Rider Cancellations

Results of regression:

Effect of Treatment on Proportion of Matched Shared Rides

	Dependent variable:
	prop_matched
treat	-0.05^{***}
commute	0.1^{***}
total_driver_payout	-0.000^{*}
rider_cancellations	0.000
treatTRUE:commute	0.01
Constant	0.7^{***}
Observations	126
R^2	0.4
Adjusted R^2	0.3
Residual Std. Error	0.1 (df = 120)
F Statistic	13.9^{***} (df = 5; 120)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Outside of rush hours, increasing wait time decreases the proportion of matched shared rides by 5 percentage points. Not sure why, could be because people are switching from Express to POOL which has a lower likelihood of matching. Coefficients in regression on total_shared, trips_pool and trips_express don't necessarily support this, but this might not be important due to averaged effects.
You can see that within rush hours increasing the wait time has no significant impact on the proportion of matched shared rides. This is consistent with the idea that within rush hours riders are committed to the type of product they will use, making them less sensitive to relative price/waiting time differences.

3- What is the effect of extending wait times from two to five minutes on driver payout per trip?
Define driver payout per trip as total_driver_payout / total_shared
Run a linear regression with interactive term between commute and treatment.
Regression results:

Effect of Treatment on Driver Payout per Trip

	Dependent variable:	
	payout_per_trip	total_driver_payout
	(1)	(2)
treat	-0.5***	-2,552.2***
commute	0.9***	3,824.9**
rider_cancellations	0.001	48.3***
total_matches	-0.000**	1.8*
total_double_matches	0.000	2.0*
treatTRUE:commute	0.1	-3,409.7**
Constant	7.9***	13,432.9***
Observations	126	126
R^2	0.3	0.7
Adjusted R^2	0.2	0.7
Residual Std. Error (df = 119)	0.6	2,837.5
F Statistic (df = 6; 119)	6.6***	57.1***
Note:		*p<0.1; **p<0.05; ***p<0.01

Note: data dictionary defines total_driver_payout as being equal to Uber's total costs for matching trips in the current time. This is because Uber's costs come from paying its drivers.

We can see that outside of rush hours increasing wait time decreases payout per trip and total payout, meaning that Uber's costs decrease. The substitution away from Express and towards POOL is more than offset by the additional efficiency generated by giving the matching algorithm more time to work with. Inside of rush hour, it does not appear to be a significant effect on payout per trip, however there is a significant effect on total driver payout.

We would recommend Stock to increase the waiting time from 2 to 5 minutes as soon he launches the experiment to avoid losing $1.6 million in the six treatment cities. However, as the data analysis revealed they should only consider increasing the waiting time during the rush hours window to maximize profit. Even though this strategy may slightly affect the number of rides cancellations, we believe riders in the rush not willing to wait or walk for a short distance may often tend to use other Uber's services available in that specific area. This may also be a good strategy in terms of marketing to advertise and push frequent Express riders to consider using other services that Uber offers on their app.

During rush hours, riders' demand will increase; this will allow Uber matching algorithm to perform well and provide more efficient shared rides to customers.