MS in Applied Data Science
Syracuse University
Portfolio Milestone

ALLAN FLORES

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Background

- B.S. in Industrial Engineering
- Supply Chain Management Director
- Monde Nissin Corporation, Mead Johnson Nutrition, Nestle, Sanofi, Novartis, Saputo Foods Dairy

Project Covered

- Kobe Bryant Shot Selection (Big Data - Python)
- Inbound Crossing at the US-MEXICO AND US-CANADA Border (Visualization - R)
- Investing in Top 3 Zip Codes (Time Series Analysis - Python)

Kobe Bryant
Shot Prediction and
Financial Impact to Lakers

Motivation

Sports analytics has become a popular topic in the data science field where the term has been popularized with the release of the 2011 film, Moneyball.

The game of sports maybe different among popular sports of baseball, hockey, football, and basketball, but the underlying principle governing the idea of analyzing and predicting outcome in sports performance is identical.

Kobe Bryant was an icon in the history of basketball and we want to leverage on data collected from his entire career.

Therefore, we would like to get an experience in sports analytics.

Business Questions

Using Kobe Bryant's stats throughout 20 years of his NBA career, we want to build several models to predict whether his shot will make or miss it.

The other part of our project is to determine if there is any correlation between Kobe Bryant's performance and the revenue and profitability of the NBA team LA Lakers using exploratory and/or Machine Learning Techniques.

Collection of Data – 2 Parts

Part 1 - Analyses of shots made by Kobe Bryant (sourced from Kaggle dataset).

Part 2 – Analyses of Kobe's performance in relation to team's performance, revenue and profitability.

The Collection of Data – Part 1

Kobe Bryant Shot Selection Data

- Primary source of dataset is from Kaggle competition titled. “Kobe Bryant Shot Selection” (https://www.kaggle.com/c/kobe-bryant-shot-selection/overview/description) for the player’s statistics.
  - Each of the observation represents a shot taken by Kobe Bryant over the data collection period.
  - Period covered from years 1996 to 2015

Column	Sample Data
action_type	Slam Dunk Shot
combined_shot_type	Dunk
game_event_id	253
game_id	20000068
lat	34.0443
loc_x	-1
loc_y	0
lon	-118.2708
minutes_remaining	7
period	3
playoffs	0
season	2000-01
seconds_remaining	53
shot_distance	0
shot_made_flag	1
shot_type	2PT Field Goal
shot_zone_area	Center(C)
shot_zone_basic	Restricted Area
shot_zone_range	Less Than 8 ft.
team_id	1610612747
team_name	Los Angeles Lakers
game_date	36838
matchup	LAL @ SAS
opponent	SAS
shot_id	102

Pre-Processing and Data Cleaning – Part 1

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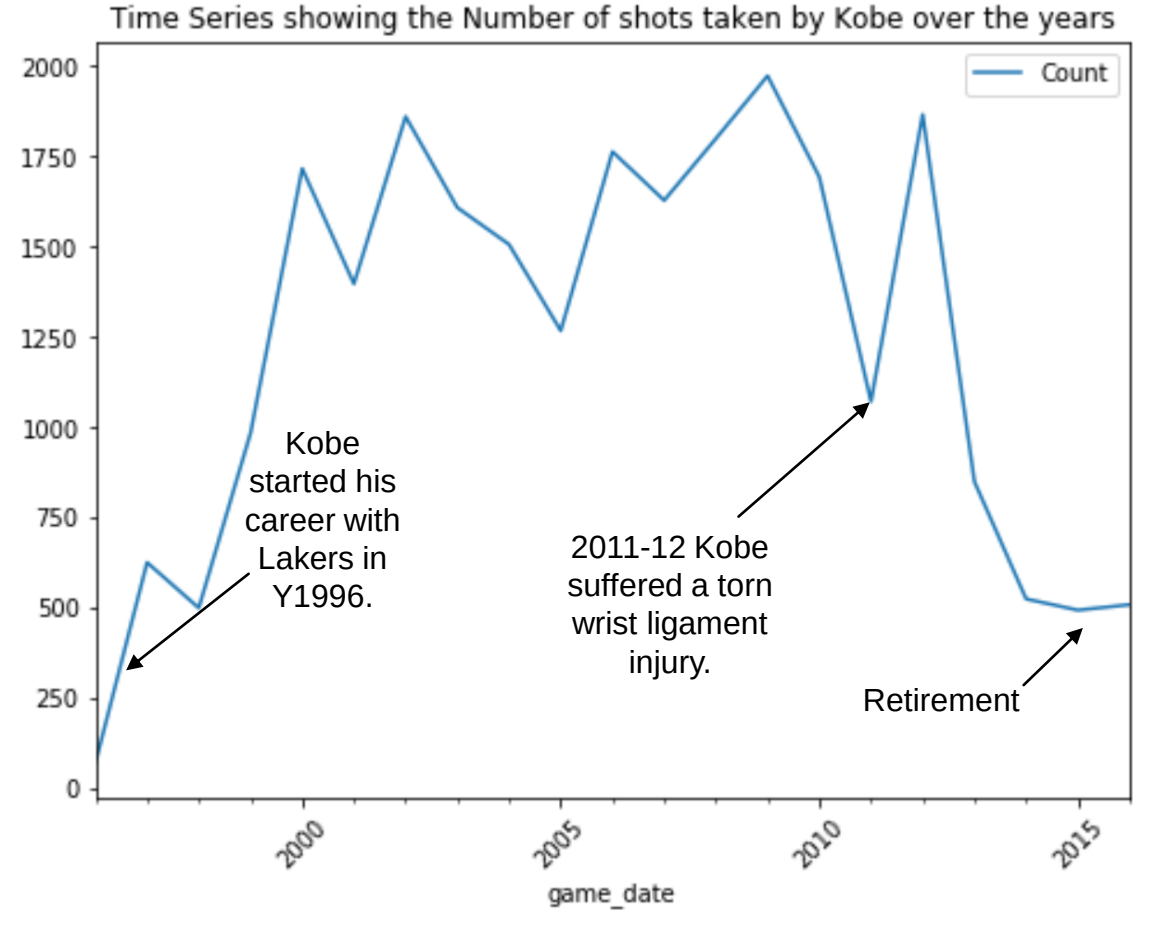
game_date	36838
matchup	LAL @ SAS
opponent	SAS
shot_id	102

- Removed from the dataframe for column, “shot_made_flag” with null values leaving us 25,697 shots from 30,697.
- This is 16% reduction from the original number of observations.
- Converted game date to date time variable for future analyses.
- Grouped game date at yearly level to plot the number of games per year.

Exploring the Dataset – Part 1



There was a steady increase in the number of shots until year 2000.

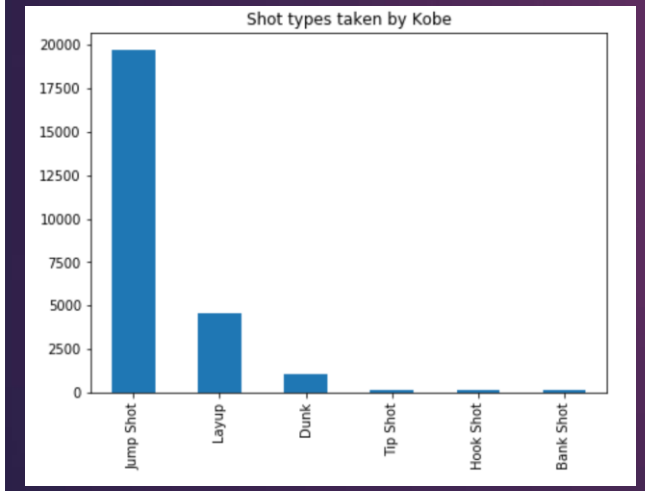
His shots stabilized with some variations from years 2000 to 2011.

His shots started to decline in Y2011 until his retirement in Y2016.

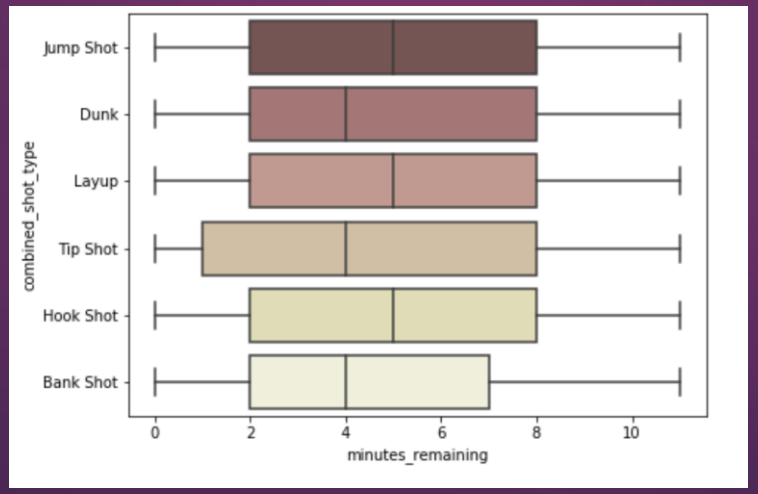
It was around Y2011-12 when Kobe suffered from a torn wrist ligament.

Exploring the Dataset – Part 1

Majority of the shot type taken by Kobe was a jump shot.

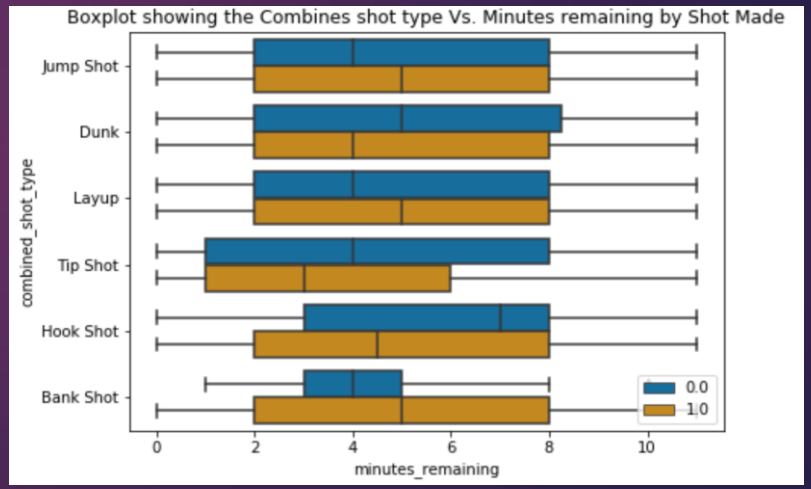


Kobe took different kinds of shots at an average of 4 – 5 minutes remaining. The tip shop had the highest distribution.



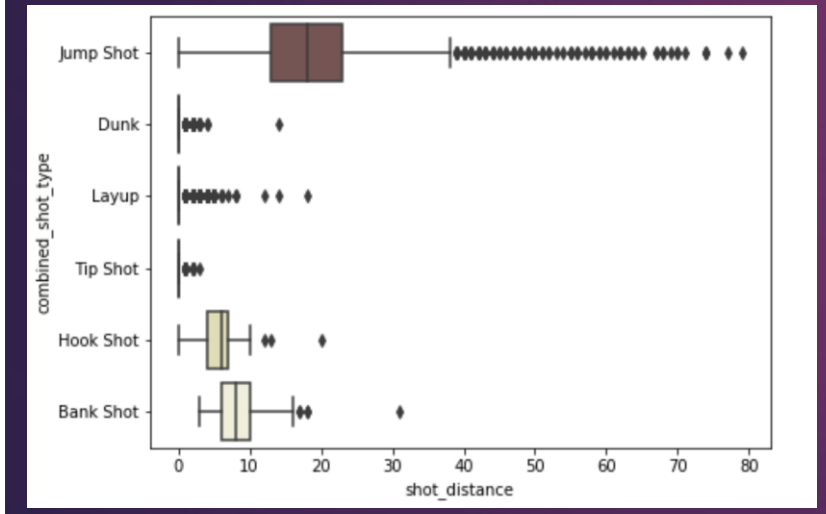
With 4 - 5 minutes remaining, the tip shop had the highest distribution, while bank shots had the lowest distribution.

Tip shots had the lowest median in terms of successful shots.

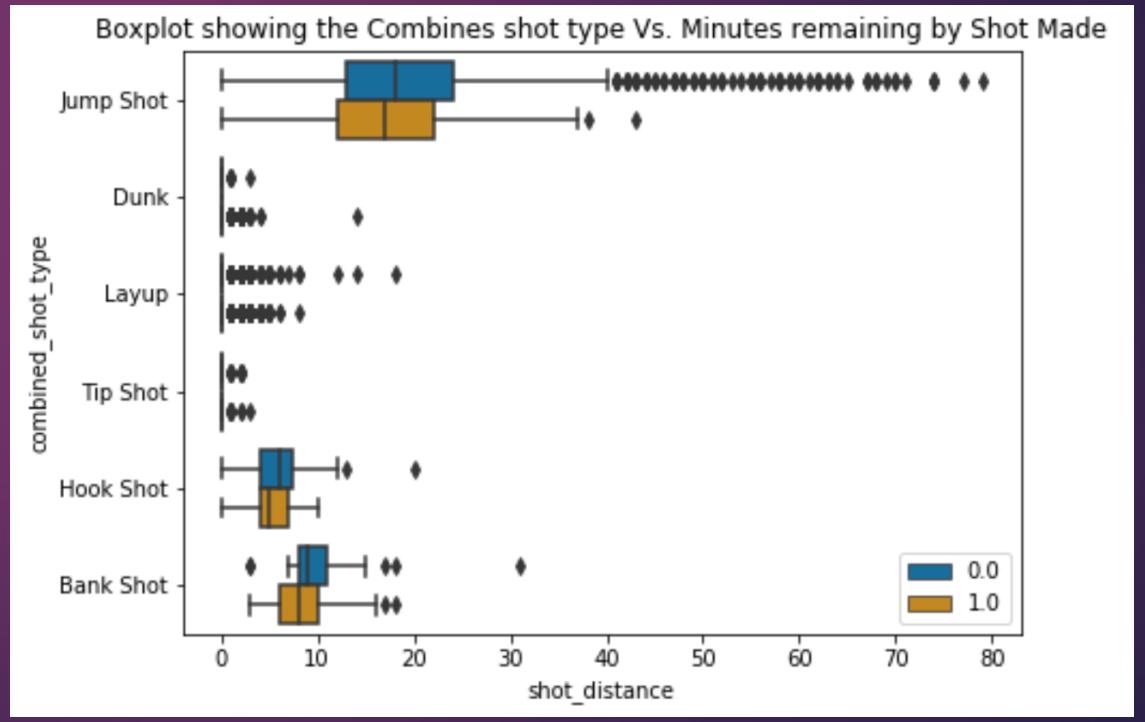


Exploring the Dataset – Part 1

Jump shot had the widest distribution in terms of distance at a median of ~20 meters away from his court.



In general, the distribution of failed shots as compared to successful shots were wider except for dunk and tip shot.

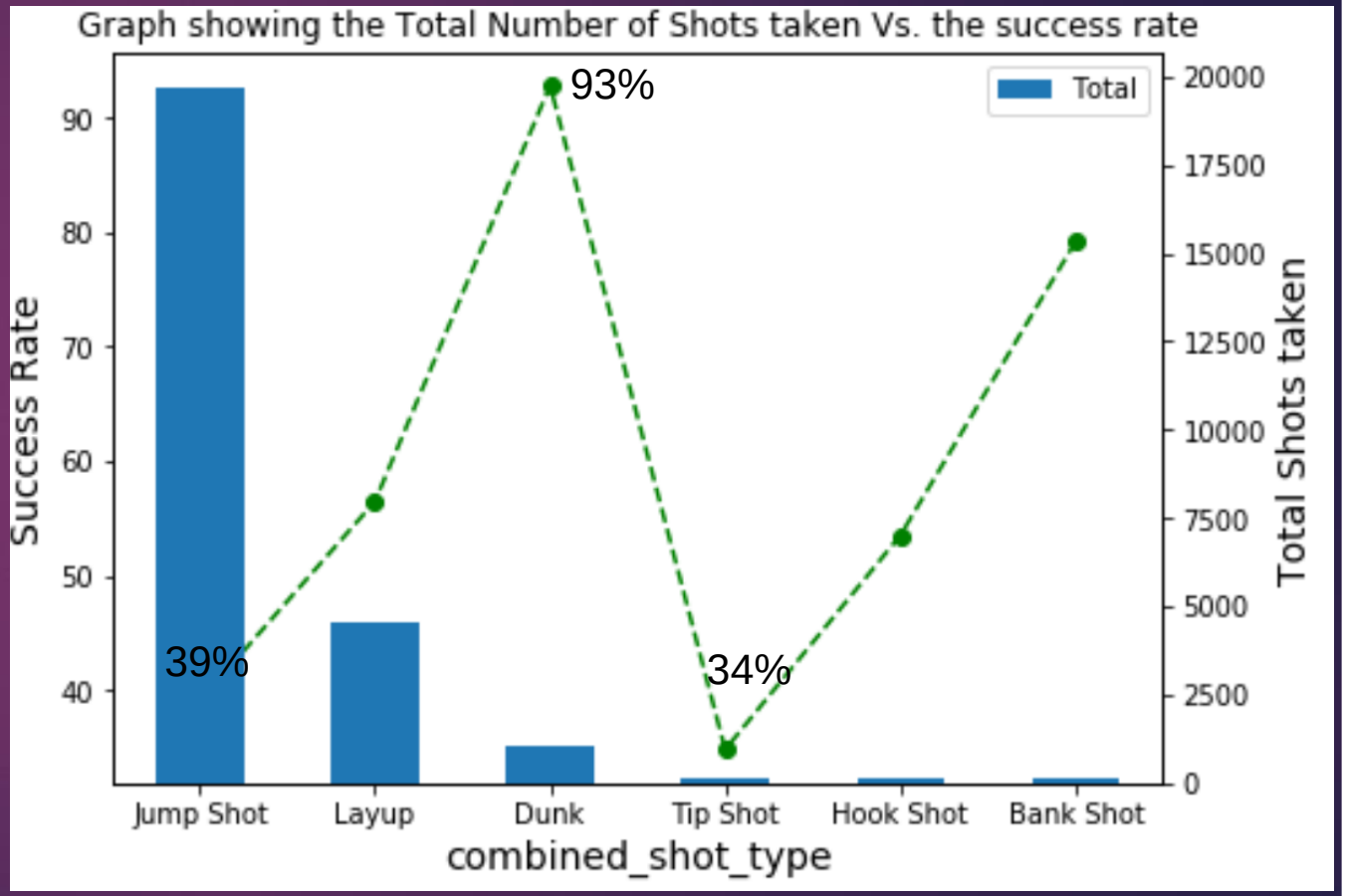


Exploring the Dataset – Part 1

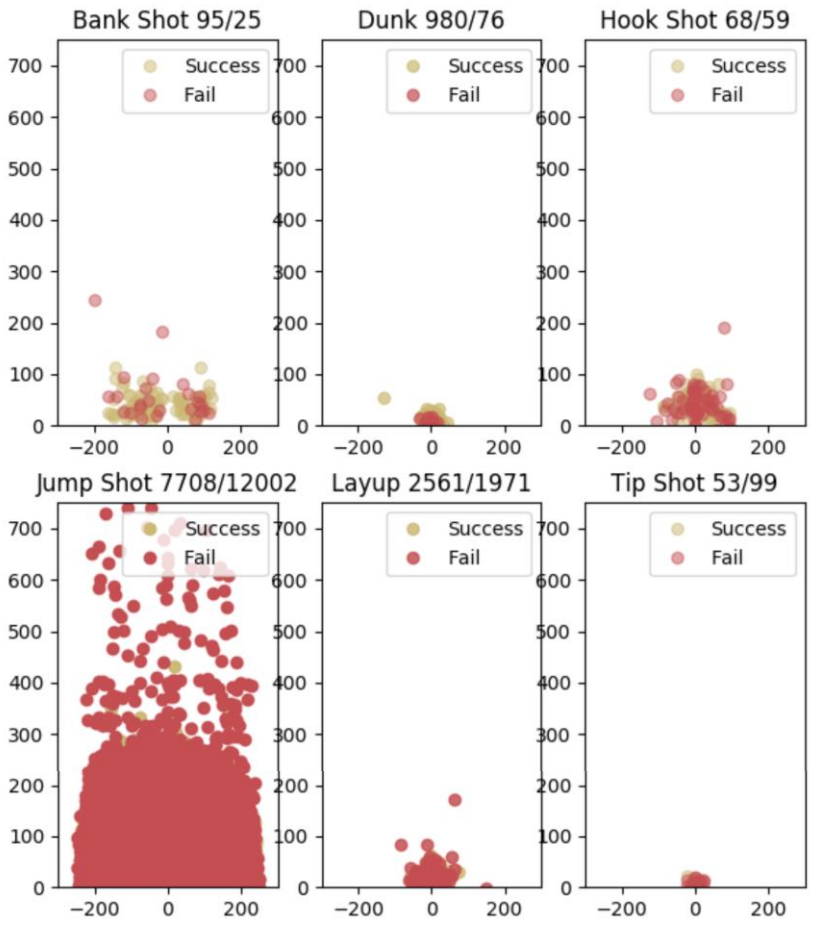
Jump shots with majority of the shots only had 39% success rate.

Tip shots had 34% success rate.

Dunk had the highest success rate of 93%.



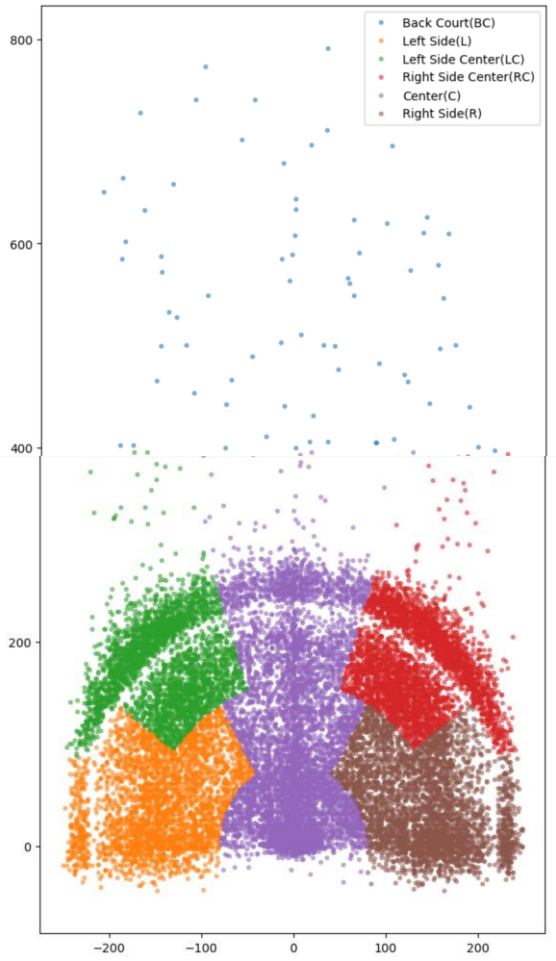
Exploring the Dataset – Part 1



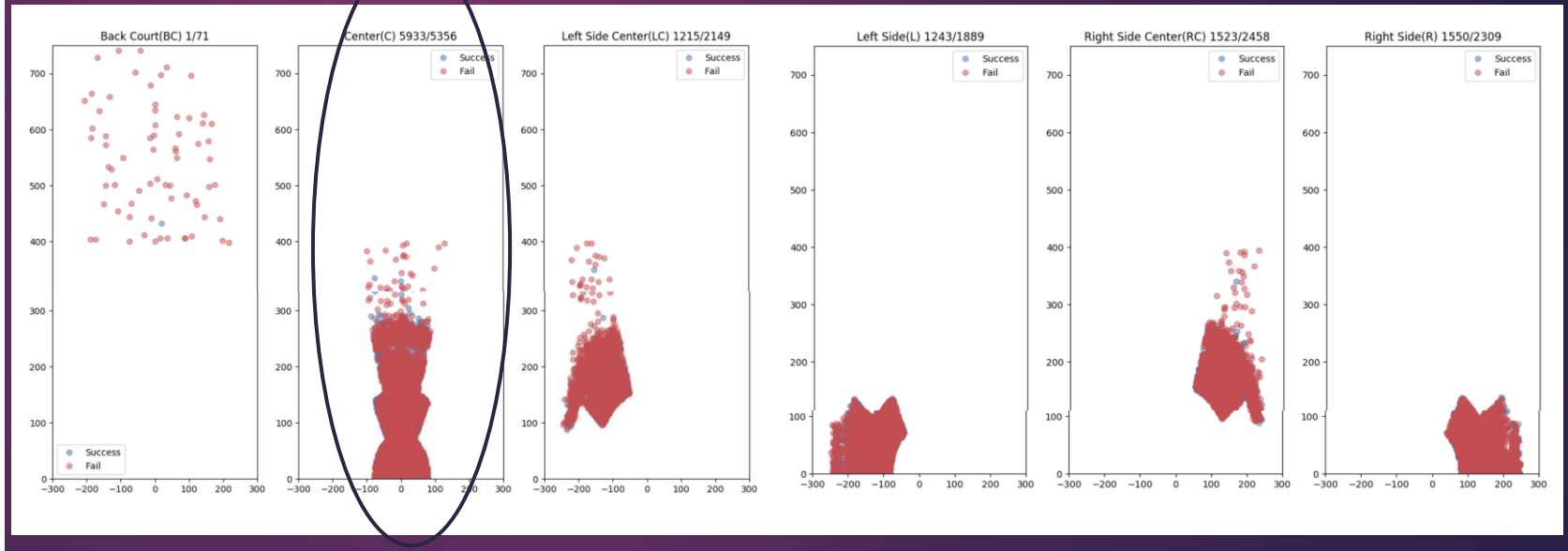
More successful shots for bank shot and dunk.

Less successful for jump shot, layup, tip shot, and hook shot.

Exploring the Dataset – Part 1

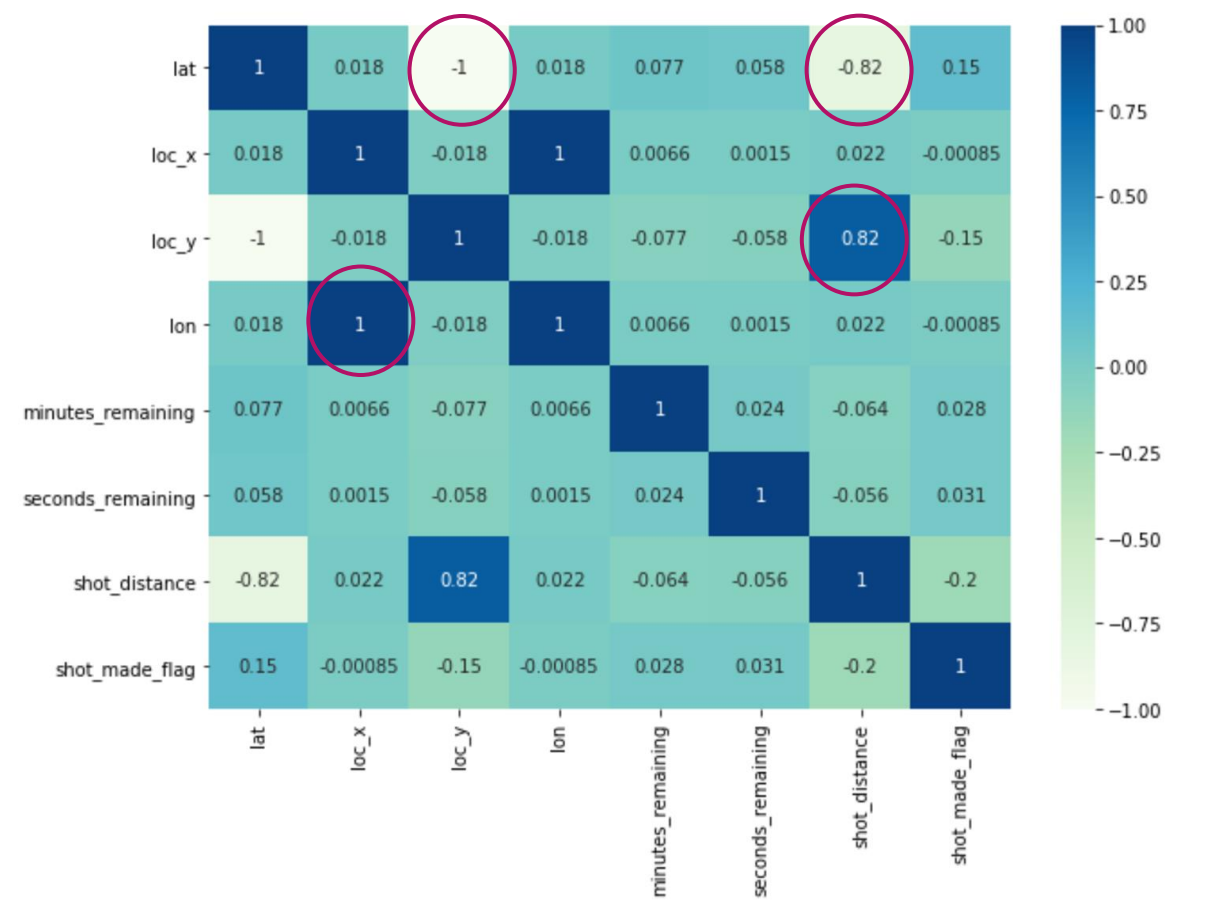


More successful shots can be seen when taken at the center of the court.



Model – Part 1

Feature Selection:



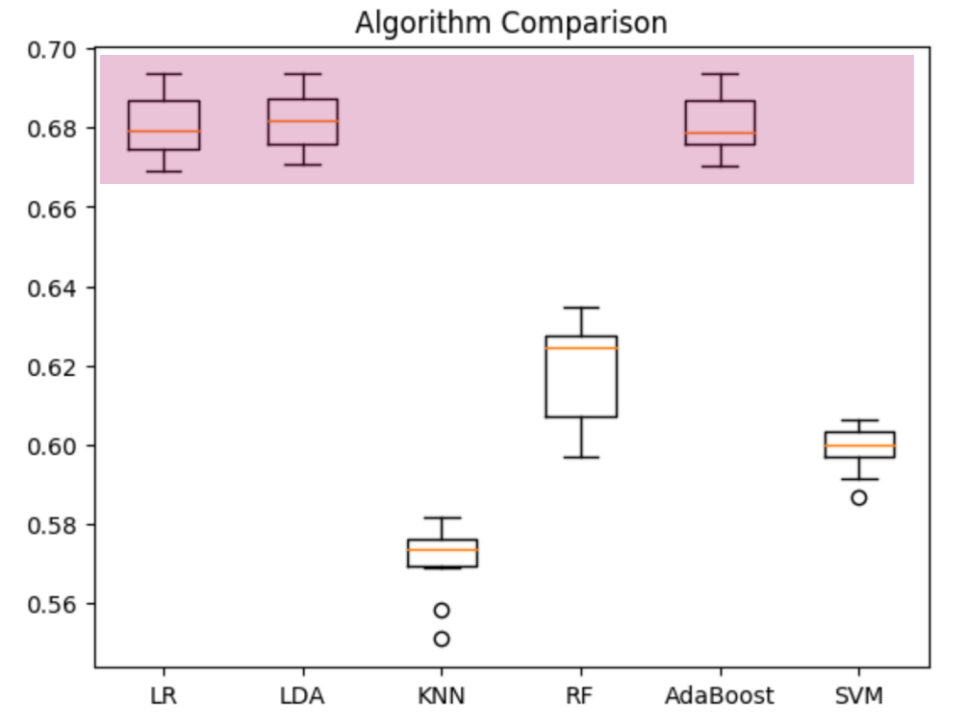
Removed highly correlated values.

lat and loc_y have a perfect negative correlation.

lon and loc_x have a perfect +ve correlation.

Shot distance is also correlated to lat and loc_y as well with a strength of -0.82 and +0.82, respectively.

Model Part 1 – LR, LDA, KNN, RF, AdaBoost, SVM



LDA, AdaBoost and LR are the most accurate models in predicting shots.

Model	Mean Accuracy	std dev
Linear Discriminant Analysis	68.15%	0.70%
Ada Boost Classifier	68.06%	0.74%
Logistics Regression	68.05%	0.73%
Random Forest Classifier	61.90%	1.23%
Support Vector Machine	59.89%	0.57%
Kneighbors Classifier	57.11%	0.90%

The Collection of Data – Part 2

Annual Income and Expense Data

- From Rodney Fort's sports financial data
  - https://sites.google.com/site/rodswebpages/codes

    redirect to : https://drive.google.com/drive/folders/1pr_yPm9oPLcfCtWOtnrLoJdvzFDbYBAk
  - Lakers financial performance by year from 1996 to 2015

Columns selected in the final data frame

season	gate_revenue	other_revenue	total_revenue	player_expense	other_expense	total_expense	operating_income	franchise_value	financial_rank
2011	74.0	123.0	197.0	76.0	73.2	149.2	47.8	1000.0	2.0
2012	94.0	201.0	295.0	110.0	118.6	228.6	66.4	1350.0	2.0
2013	96.0	197.0	293.0	89.0	99.9	188.9	104.1	2600.0	1.0
2014	98.0	206.0	304.0	76.0	94.5	170.5	133.4	2700.0	2.0
2015	99.0	234.0	333.0	84.0	129.8	213.8	119.2	3000.0	1.0

Annual Ticket Price and Fan Cost Data

- From Rodney Fort's sports financial data
  - Lakers game performance from 1996 to 2015

season	attendance	fan_cost_index	ticket_price_index	win_ratio
1996	697132	232.56	38.39	0.683
1997	691994	250.60	41.65	0.744
1998	430007	295.44	51.11	0.620
1999	771420	427.56	81.89	0.817
2000	776336	446.76	87.69	0.683

The Collection of Data – Part 2

Lakers Attendance

- Data provided by the Association of Professional Basketball Research
- https://www.apbr.org/attendance.html
- Years covered from 1960 to 2015

Columns selected in the final data frame

season	home_games	total_attended	avg_attended
2011	33	626901	18997
2012	41	778877	18997
2013	41	771974	18829
2014	41	768244	18738
2015	41	778877	18997

Lakers Annual Record

- Sourced from Sports Reference API, Robert Clark
- https://sportsreference.readthedocs.io/en/stable/nba.html
- Installed ‘sportsreference’ and chose Lakers annual records from 1996 to 2016
- Data selected:
  - Wins
  - Losses
  - Wins Ratio = Wins / (Wins + Losses) – *Derived column*

The Collection of Data – Part 2

Lakers Team Data

- Sourced from Sports Reference API, Robert Clark
- https://sportsreference.readthedocs.io/en/stable/nba.html
- Installed ‘sportsreference’ and chose Lakers annual records from 1996 to 2016

Data selected (excerpt):

	abbreviation	name	assists	blocks	defensive_rebounds	field_goal_attempts	field_goal_percentage	field_goals	free_throw_attempts	free_throw_percentage
1996	LAL	Los Angeles Lakers	2080	516	2303	6706	0.480	3216	2049	0.746
1997	LAL	Los Angeles Lakers	1845	575	2414	6642	0.454	3018	2330	0.692
1998	LAL	Los Angeles Lakers	2009	556	2471	6536	0.481	3146	2743	0.679
1999	LAL	Los Angeles Lakers	1095	287	1482	3935	0.468	1841	1503	0.683
2000	LAL	Los Angeles Lakers	1921	534	2738	6836	0.459	3137	2368	0.696

Final data selected:

TEAM
Team Rank
Team Games Played
Team Minutes Played
Team Points
Teal Total Rebounds
Team Blocks
Team Steals
Team Turnovers
Team Two Point Field Goal Attempts
Team Two Point Field Goal Percentage
Team Three Point Field Goal Attempts
Team Three Point Field Goal Percentage
Team Free Throw Attempts
Team Personal Fouls
Team Opponent Points
Team Opponent Field Goal Attempts
Team Opponent Field Goal Percentage
Team Opponent Turnovers
Team Opponent Personal Fouls

The Collection of Data – Part 2

Data selected (excerpt):

season	team_abbreviation	player_id	nationality	position	height	weight	assist_percentage	assists	block_percentage	blocks	box_plus_minus
1996	LAL	bryanko01	United States of America	SF	6-6	212	13.8	91	1.6	23	-0.1
1997	LAL	bryanko01	United States of America	SF	6-6	212	16.0	199	1.3	40	1.4
1998	LAL	bryanko01	United States of America	SF	6-6	212	17.5	190	1.9	50	2.1
1999	LAL	bryanko01	United States of America	SF	6-6	212	22.4	323	1.7	62	5.1
2000	LAL	bryanko01	United States of America	SF	6-6	212	23.0	338	1.1	43	4.8

Final data selected:

Kobe Salary
Kobe Games Started
Kobe Games Played
Kobe Minutes Played
Kobe Win Share Per 48 Minutes
Kobe Win Shares
Kobe Value Over Replacement Player
Kobe Usage Percentage
Kobe Box Plus Minus
Kobe Defensive Box Plus Minus
Kobe Offensive Box Plus Minus
Kobe Defensive Win Shares
Kobe Offensive Win Shares
Kobe True Shooting Percentage
Kobe Player Efficiency Rating
Kobe Points
Kobe Personal Fouls

Player's Career Data – Kobe Bryant Data

- From 'sportsreference.nba.roster' import Player
- Selected player, "bryanko01" to extract Kobe's statistics

Pre-Processing and Data Cleaning – Part 2

- Combined all relevant team, and Kobe data through merge function
  - Operating income and franchise value
  - Fan cost and ticket price index
  - Attendance
  - Record (wins, losses, wins ratio)
  - Team data (team statistics)
  - Kobe data (Kobe's statistics including his salary)

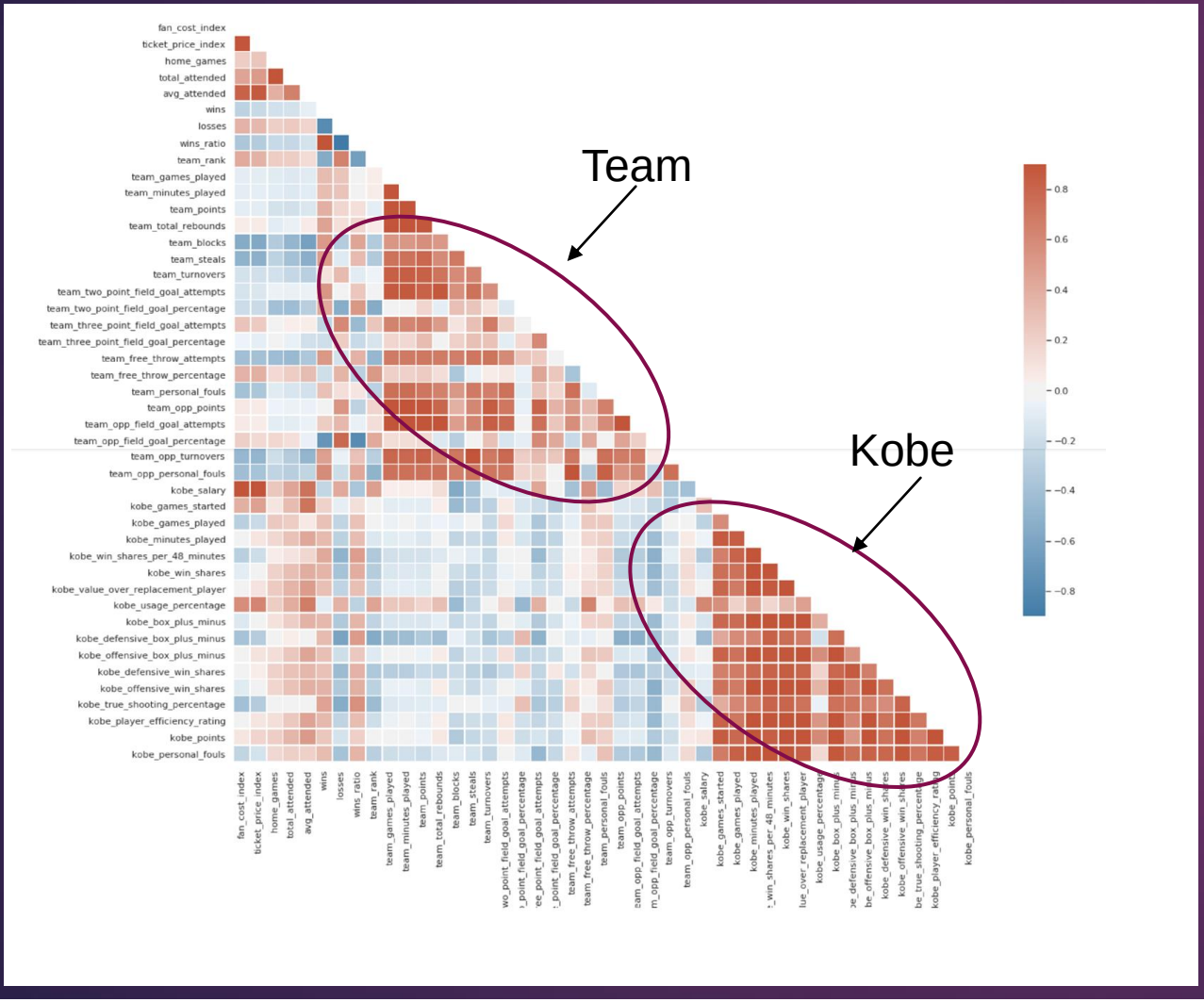
- Generated a normalized data frame to be used for some analyses

Pre-Processing and Data Cleaning – Part 2

Final Data Frame

GENERAL	TEAM	KOBE
Operating Income	Team Rank	Kobe Salary
Franchise Value	Team Games Played	Kobe Games Started
Fan Cost Index	Team Minutes Played	Kobe Games Played
Ticket Price Index	Team Points	Kobe Minutes Played
Home Games	Teal Total Rebounds	Kobe Win Share Per 48 Minutes
Total Attended	Team Blocks	Kobe Win Shares
Average Attended	Team Steals	Kobe Value Over Replacement Player
Wins	Team Turnovers	Kobe Usage Percentage
Losses	Team Two Point Field Goal Attempts	Kobe Box Plus Minus
Wins Ratio	Team Two Point Field Goal Percentage	Kobe Defensive Box Plus Minus
	Team Three Point Field Goal Attempts	Kobe Offensive Box Plus Minus
	Team Three Point Field Goal Percentage	Kobe Defensive Win Shares
	Team Free Throw Attempts	Kobe Offensive Win Shares
	Team Personal Fouls	Kobe True Shooting Percentage
	Team Opponent Points	Kobe Player Efficiency Rating
	Team Opponent Field Goal Attempts	Kobe Points
	Team Opponent Field Goal Percentage	Kobe Personal Fouls
	Team Opponent Turnovers	
	Team Opponent Personal Fouls	

Exploring the Dataset – Part 2



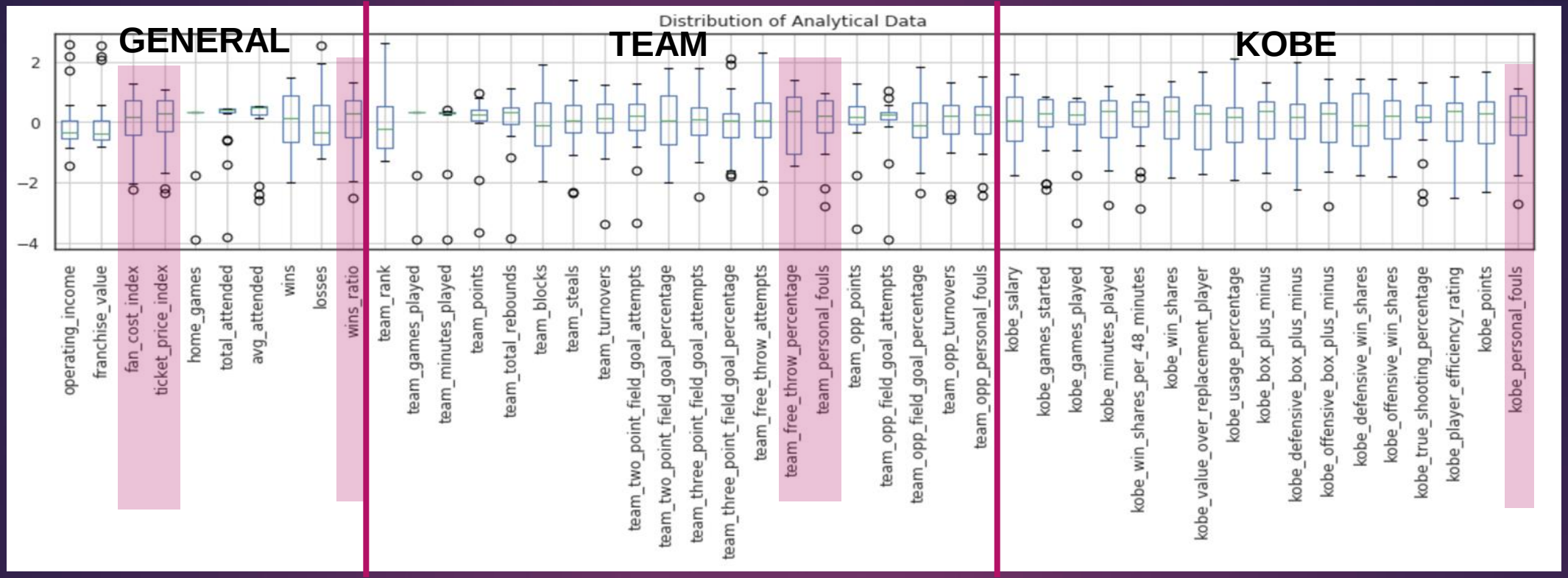
The team performance are correlated with itself and not with Kobe's.

Ticket prices and general fan costs are positively correlated with Kobe's salary.

Opponent's field goal % is closely correlated with Lakers' wins and losses.

Avg. attendance is slightly negatively correlated with team blocks and slightly positively correlated with Kobe's games played.

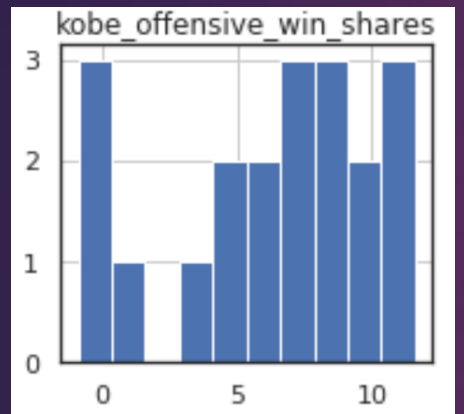
Exploring the Dataset – Part 2

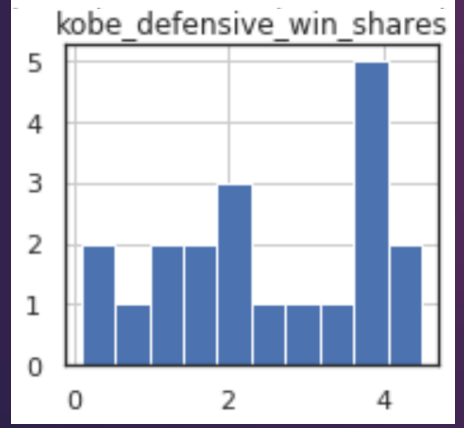


- Most team performance are normally distributed except for personal fouls and free throw percentage.
- Ticket price and fan cost indices are negatively skewed, but attendance varies only slightly throughout time.
- Most of the Lakers final ranking are on the lower side outside of some good years.
- Kobe's statistics are all relatively normally distributed expect for personal fouls, that are negatively skewed.
- All aggregate measures of Kobe's performance show positive results for most of his career.

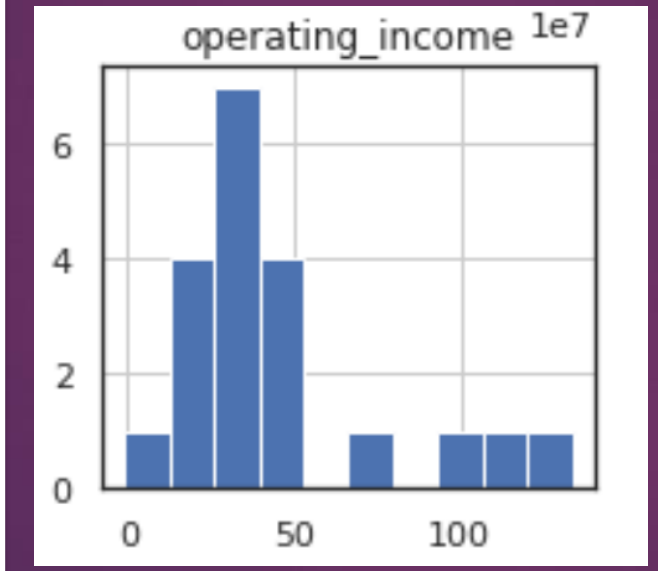
Exploring the Dataset – Part 2

Kobe appears to have a stronger offensive win shares rate than defensive win shares rate.

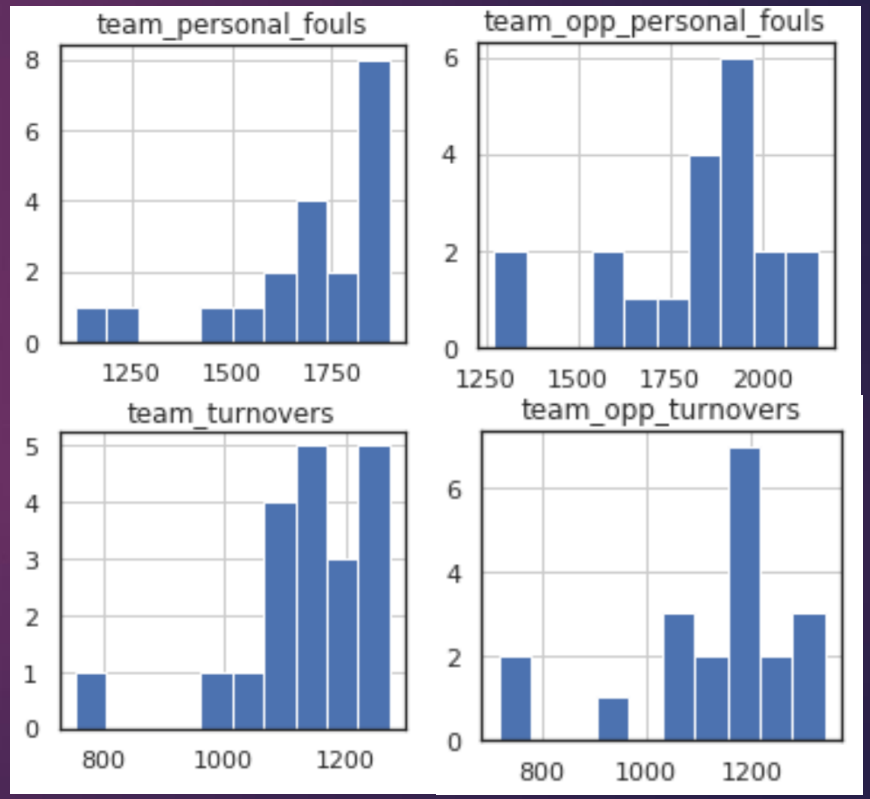




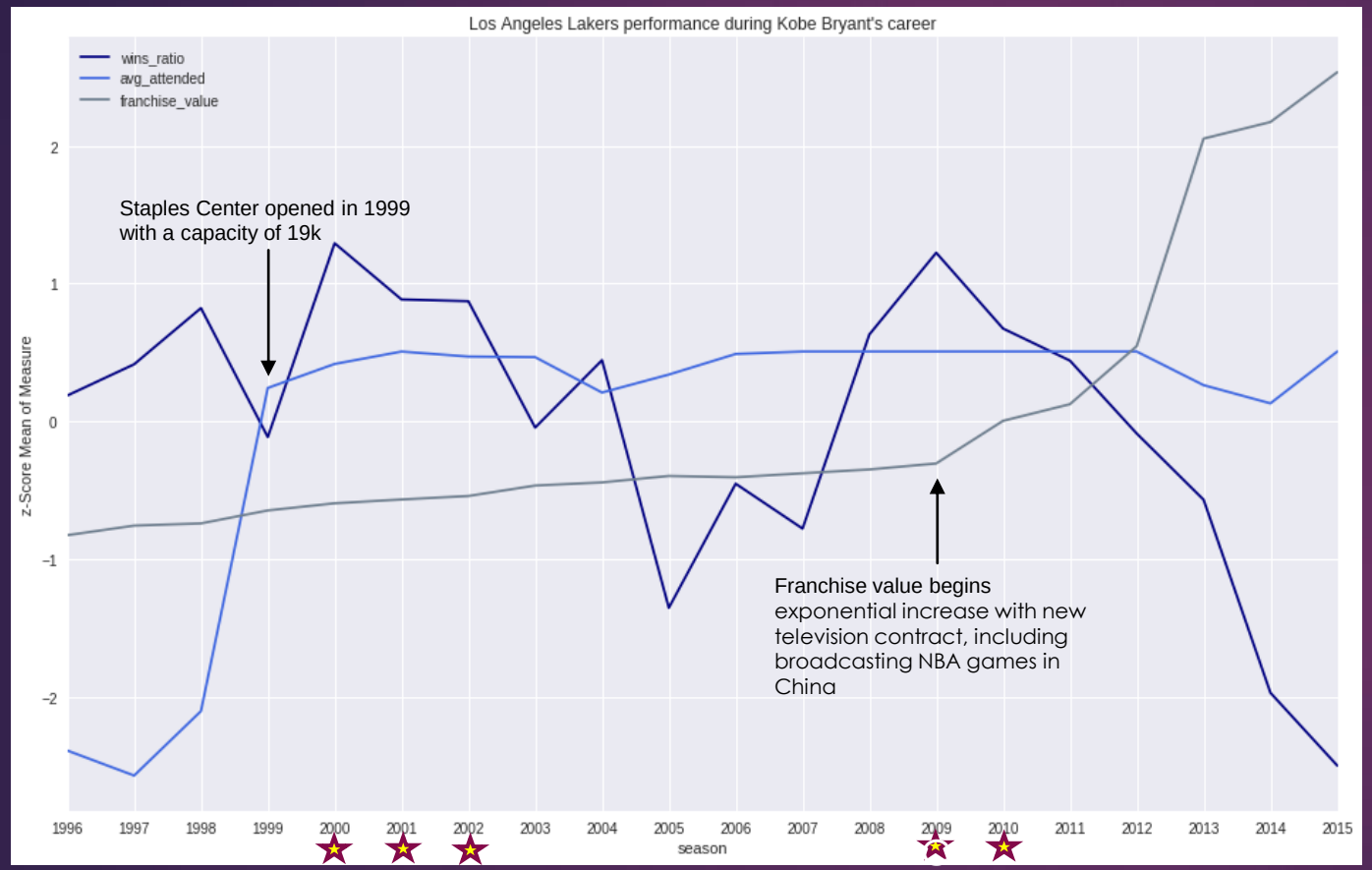
Operating income centralizes between $0 to $50M during most years except for four high years.



Team personal fouls and turnovers are negatively skewed, more so than their opponents.



Exploring the Dataset – Part 2



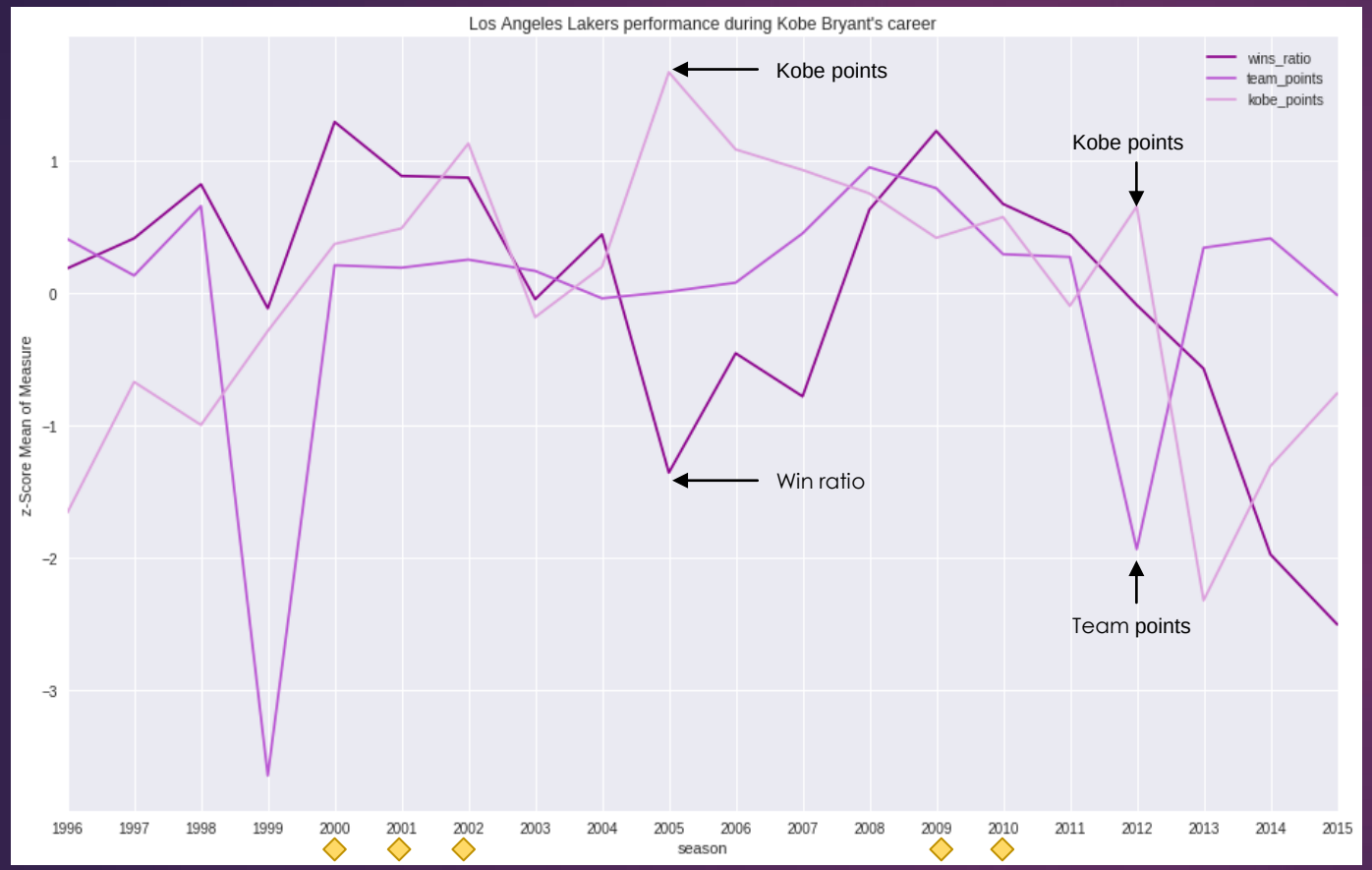
Average attendance totals appear to be relatively flat throughout much of Kobe's career.

Franchise value increases steadily from 1996, with an exponential increase starting in 2009.

Franchise value appears unaffected by changes in attendance, wins, etc.

Attendance appears to fluctuate most at the end of Kobe' career.

Exploring the Dataset – Part 2



Team wins fell off sharply toward the end of Kobe's career, more often from his injuries and inversion of points.

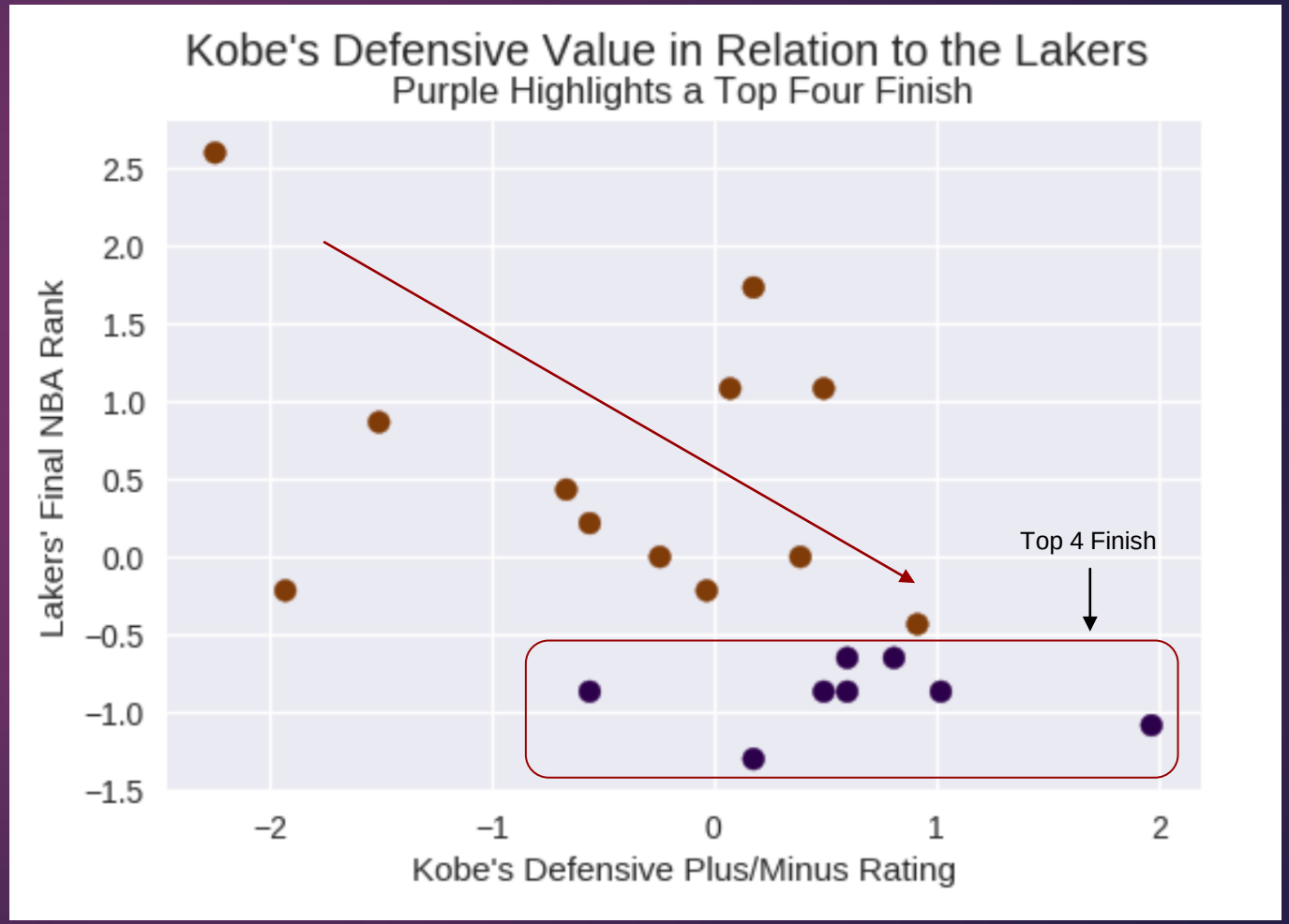
Kobe's points were inverted from team points in most of the final years of his career.

The first year at the Staples Center showcased a mediocre lack of team wins and the lowest amount of team points throughout all of Kobe's career.

Exploring the Dataset – Part 2

Kobe's defensive performance appears to be linearly correlated with better overall team performance (as measured by final NBA rank).

The linear relationship is not perfect, but does highlight an overall trend in most years. This measure can be affected by additional support from other star players on the Lakers (ex. Shaquille O'Neal)



Model – OLS Regression – Part 2

Version	Description	R-squared
Version 1.0	First run	0.846
Version 1.1	Top 3 highest p-values removed	0.754
Version 1.2	Next top 2 highest p-values	0.712
Version 1.3	P-value above 0.1 removed	0.694
Version 1.4	P-value above 0.05 removed	0.692

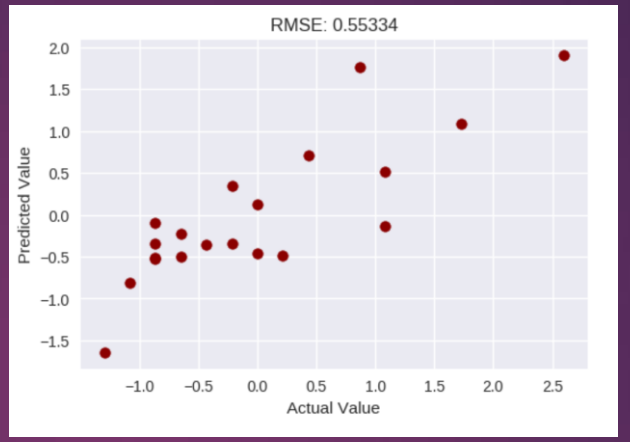
Version 1.4:

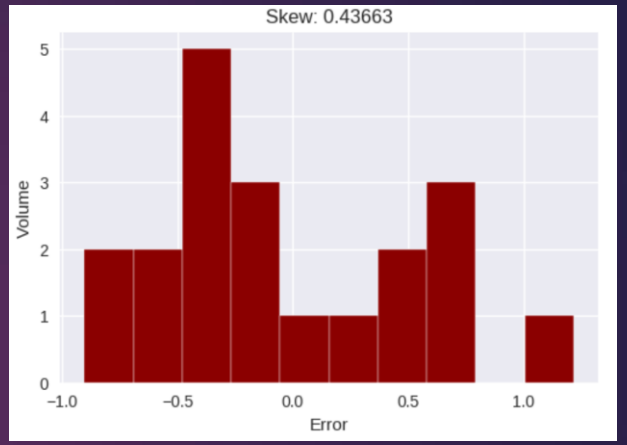
OLS Regression Results

Dep. Variable:	team_rank	R-squared:	0.692
Model:	OLS	Adj. R-squared:	0.549
Method:	Least Squares	F-statistic:	4.860
Date:	Thu, 05 Mar 2020	Prob (F-statistic):	0.00819
Time:	02:12:35	Log-Likelihood:	-16.613
No. Observations:	20	AIC:	47.23
Df Residuals:	13	BIC:	54.20
Df Model:	6		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-3.469e-18	0.154	-2.25e-17	1.000	-0.333	0.333
team_blocks	0.1527	0.261	0.586	0.568	-0.410	0.716
team_turnovers	0.2646	0.276	0.959	0.355	-0.331	0.861
team_free_throw_attempts	-0.8256	0.281	-2.937	0.012	-1.433	-0.218
team_personal_fouls	0.0500	0.265	0.189	0.853	-0.522	0.622
kobe_games_started	0.3366	0.223	1.512	0.154	-0.144	0.818
kobe_defensive_box_plus_minus	-0.6817	0.199	-3.420	0.005	-1.112	-0.251

Omnibus:	0.975	Durbin-Watson:	2.252
Prob(Omnibus):	0.614	Jarque-Bera (JB):	0.896
Skew:	0.440	Prob(JB):	0.639
Kurtosis:	2.453	Cond. No.	3.94





Linear relationship exists between Kobe's and the Lakers performance and the final NBA ranking.

Team Free Throw Attempts and Kobe's Defensive Plus or Minus Ratio are the strongest predictors.

Model underpredicts by approximately half of a std dev.

RMSE is bimodal with a higher propensity to predict a slightly better than actual rank.

Time Series – Part 2

Prior to the opening of the Staples Center, the Lakers could have experienced a variety of attendance results. The time series was not stationary, even after log transformation.

As shown below, four periods of attendance change occurred from 1970 through 1993. If included the opening of the Staples Center, in 1999, would have been noted as a significant change.

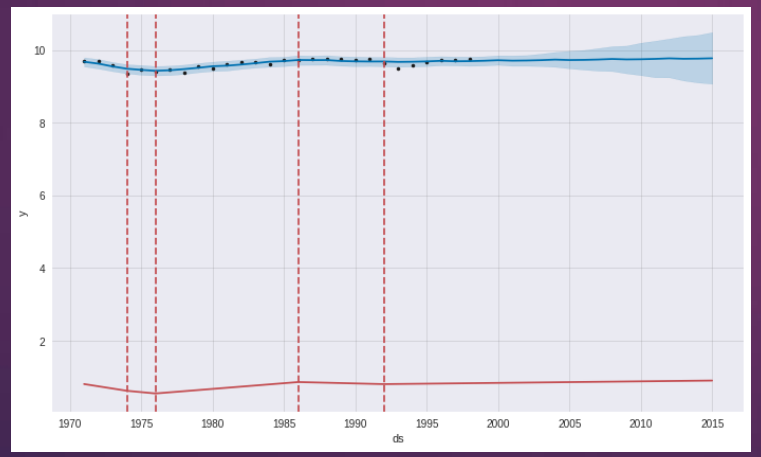
The Lakers ultimately averaged a near-sellout during the peak of Kobe's career, only slightly decreasing at the tail end. The FB Prophet forecast produced a RMSE of +1,424 people from '99.

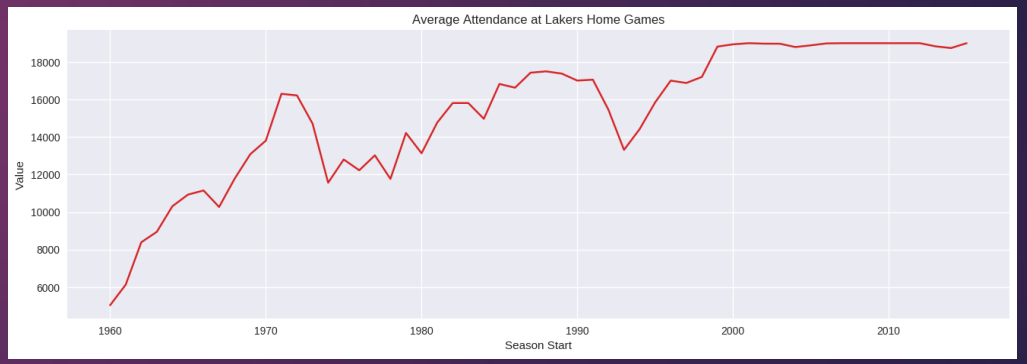
```
-- ACTUAL DATA VALUES --
ADF Statistic: -1.884731
p-value: 0.339278

-- Critical Values --
1%: -3.578
5%: -2.925
10%: -2.601


-- LOG TRANSFORMED (e) DATA VALUES --
ADF Statistic: -2.091609
p-value: 0.247902

-- Critical Values --
1%: -3.578
5%: -2.925
10%: -2.601
```



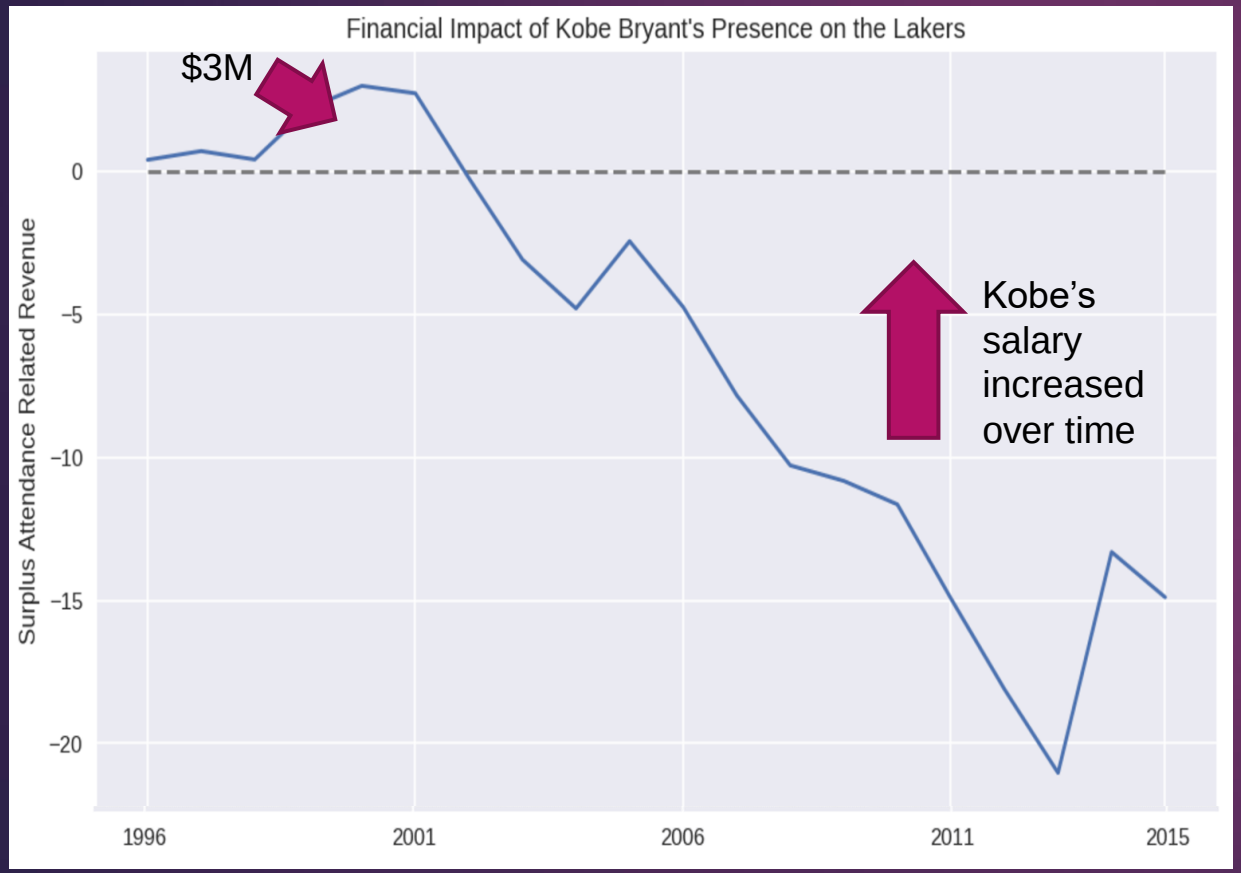


Data Source: Attendance – Part 2

Exploring the Dataset – Part 2


```
# Create a calcualted ticket revenue surplus, sans Kobe's Salary
finance['kobe_surplus'] = ((finance.home_games * finance.error * finance.fan_cost_index * (finance.kobe_usage_percentage / 100)) - finance.kobe_salary) / 1000000
```

Million USD



Given that Kobe's play, especially defensively, made an impact on the overall team performance **and** overall team performance draws attention to the franchise (ex. attendance, merchandise sales, etc.):

- The financial impact of Kobe Bryant is being assessed as the difference between expected and actual attendance, weighted by Kobe's use throughout the season (minutes played, injuries, etc.), and reduced by Kobe's salary.
- This measure shows a net gain for Lakers from 1996 through 2002, then declining through the end of Kobe's career as his salary increases.
- Even though the Lakers won five championships throughout Kobe's career (2000 - 2002, 2009, 2010), an attendance capacity diminishes the financial impact of one player.
- Albeit, this is a conservative view of a player's financial impact.

Conclusion

Kobe's jump shots with majority of the shots only had 39% success rate, while dunk had the highest success rate at 93%.

Shot were more successful when executed from the center of the court.

Ticket prices and general fans costs were positively correlated with Kobe's salary.

Attendance grew sharply with the opening of Staples Center, and held flat throughout Kobe's career.

Kobe created a "surplus" of $3M during 2000 – 2001 season, winning the NBA championship.

The surplus Kobe created started to decline in Y2002 until his retirement, but Lakers franchise value started to increase in Y2010.

Recommendations

Explore the upward trend of the franchise value after Y2010 .

Comparison of his statistics and impact to team's profitability as compared to other basketball legends and teams
(e.g. Michael Jordan, LeBron James, 1988 to 1990 Detroit Pistons, etc.).

Kobe's defensive winning style as compared to other player's style in winning a game.

Extrapolate on how a weighted shot has an impact to overall team win as compared to other measurements.

Extrapolate how intermingling younger players, with lower salaries, can augment star players to create a cost effective but high performing (championship) team.

Three Zip Codes in the US to Invest

Motivation

Volatility of the housing market in the US.

Application of latest technique in forecasting with data science.

Business Questions

Which three zip codes to invest given historical data and other factors to consider.

Factors to consider in recommending a decision.

The Collection of Data

Zillow Median Home Values

- files.zillowstatic.com/research/public/Zip/Zip_Zhvi_SingleFamilyResidence.csv

Median Household Income for Y2018

- https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/

Crime Rates and Population

- Extracted from Kaggle with Y2016 crime rates by county in the United States. Title from Kaggle: “United States Crime Rate by County

Pre-Processing and Data Cleaning

Dealing with Missing Values, Cleaning and Transforming Data

Zillow Data:

- Dropped data from Apr 1996 to Dec 1996.
- Added “Growth” rate column by taking the Dec 2019 data and dividing it by the Jan 1997 data.
- Added “std” or standard deviation column by taking data for the past 10 years from Jan 2010 to Dec 2019.
- Added “mean” column by taking data for the past 10 years from Jan 2010 to Dec 2019.

Median Household Income for Y2018:

- Retained only columns County Name, State and Median Income.

Crime Rates:

- Retained only columns County Name, State and Crime Rate Income.

Pre-Processing and Data Cleaning

Merging of Data

First merge:

- Merged Zillow and Crime Rate data frames joining through “County Name” and “State” columns.
- 746 observations were dropped from 30,434 to 29,688.

Second merge:

- Merged “First merge” with the Median Household Income joining through “County Name” and “State” columns.
- This time, 29,519 observations were left or only 169 observations were dropped from the first merge.

Pre-Processing and Data Cleaning

Further Cleaning Transformation After Merging Data

- Kept rows with at least 60% non-NA values, which resulted to 23,044 observations left.
- Removed rows with crime rates of more than 1.27% (taken from 25% quantile of Crime Rate data), which resulted to 3,954 observations.
- Removed rows with median income of at most $59,000 (taken from 75% quantile of Median Household Income data), which resulted to 1,151 observations.

Pre-Processing and Data Cleaning

Transformation After Choosing Top 10 Zip Codes

- Dates as columns had been reset as index.
- Re-assigned index as “ds” which is a requirement in using fbprophet.
- Converted new index to datetime.
- Re-assigned zip codes as “y.”
- Generated fbprophet output **functions** (can be seen from Jupyter Notebook file) for the Top 10 Zip Codes

Exploratory Data Analysis

Best 20 Zipcodes:

	RegionName	Metro	CountyName	City	State	Growth	mean	std
2331	90403	Los Angeles-Long Beach-Anaheim	Los Angeles County	Santa Monica	CA	13.914982	1.092774e+06	518560.866240
9350	91108	Los Angeles-Long Beach-Anaheim	Los Angeles County	San Marino	CA	13.776618	9.497870e+05	470036.233530
9981	90211	Los Angeles-Long Beach-Anaheim	Los Angeles County	Beverly Hills	CA	12.554974	9.871943e+05	494881.970778
1088	90020	Los Angeles-Long Beach-Anaheim	Los Angeles County	Los Angeles	CA	12.272559	1.488784e+06	635028.946798
331	90027	Los Angeles-Long Beach-Anaheim	Los Angeles County	Los Angeles	CA	11.977903	7.680990e+05	335516.443857
253	90004	Los Angeles-Long Beach-Anaheim	Los Angeles County	Los Angeles	CA	11.318958	7.775213e+05	338011.493077
2251	90266	Los Angeles-Long Beach-Anaheim	Los Angeles County	Manhattan Beach	CA	10.948580	1.071792e+06	507941.211850
2733	90048	Los Angeles-Long Beach-Anaheim	Los Angeles County	Los Angeles	CA	10.497167	9.961686e+05	406054.897367
1626	94610	San Francisco-Oakland-Hayward	Alameda County	Oakland	CA	10.286459	8.363412e+05	401629.738911
4468	91030	Los Angeles-Long Beach-Anaheim	Los Angeles County	South Pasadena	CA	10.195877	6.273837e+05	268614.706156
2106	90069	Los Angeles-Long Beach-Anaheim	Los Angeles County	West Hollywood	CA	9.604911	1.297958e+06	533324.387651
7396	90212	Los Angeles-Long Beach-Anaheim	Los Angeles County	Beverly Hills	CA	9.271800	1.453807e+06	614666.562734
43	90046	Los Angeles-Long Beach-Anaheim	Los Angeles County	Los Angeles	CA	9.170598	9.438518e+05	372731.539802
1307	90005	Los Angeles-Long Beach-Anaheim	Los Angeles County	Los Angeles	CA	9.067142	8.978202e+05	344777.433684
589	90036	Los Angeles-Long Beach-Anaheim	Los Angeles County	Los Angeles	CA	8.657940	9.829735e+05	378354.297132
2032	90291	Los Angeles-Long Beach-Anaheim	Los Angeles County	Los Angeles	CA	8.409081	1.038788e+06	412799.270720
514	11216	New York-Newark-Jersey City	Kings County	New York	NY	8.332922	1.047424e+06	381081.572991
2814	90068	Los Angeles-Long Beach-Anaheim	Los Angeles County	Los Angeles	CA	8.272667	8.431533e+05	319368.055118
5310	90210	Los Angeles-Long Beach-Anaheim	Los Angeles County	Beverly Hills	CA	8.216722	2.298412e+06	868016.499644
8143	90401	Los Angeles-Long Beach-Anaheim	Los Angeles County	Santa Monica	CA	8.152619	1.228189e+06	414800.255759

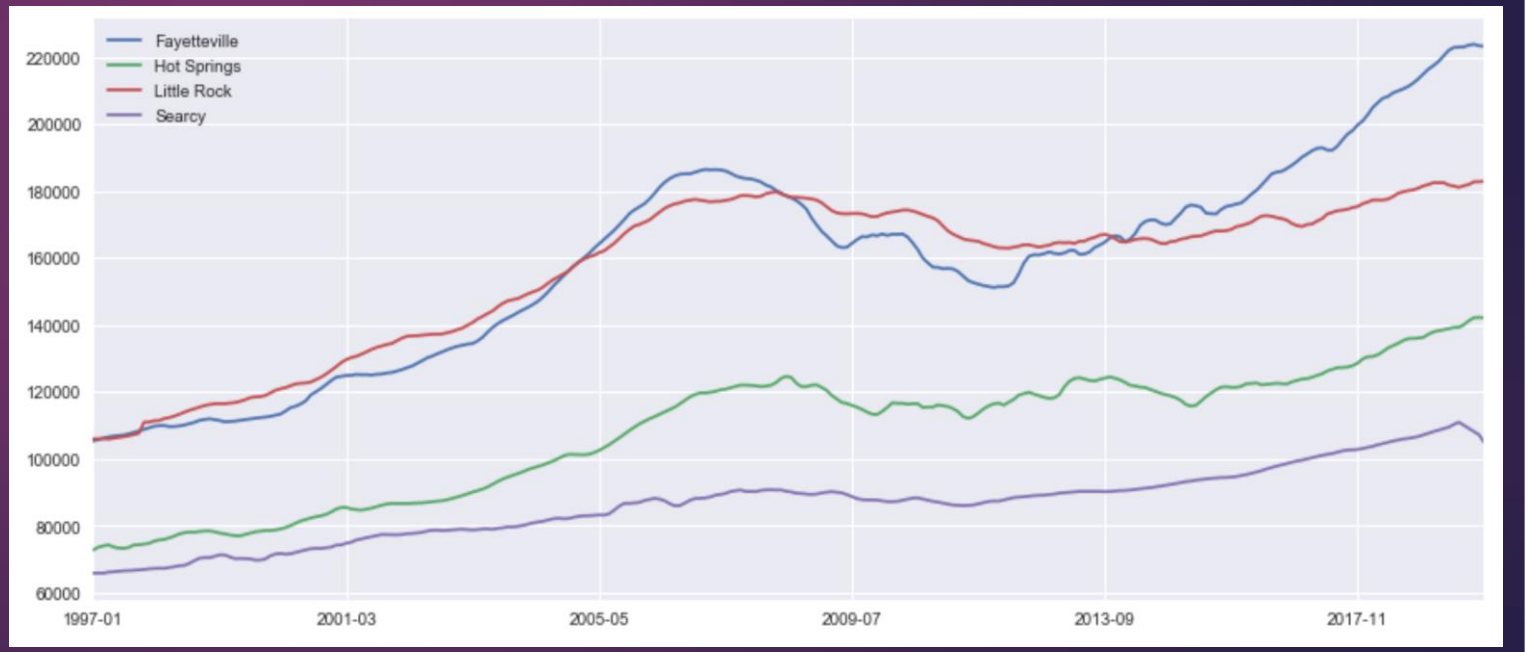
From the top 20 zip codes nationwide based on growth rates, majority of the zip code were all out of California and only 1 few from New York.

Exploratory Data Analysis

Time Series plot for Hot Springs, Little Rock, Fayetteville, and Searcy in Arkansas.

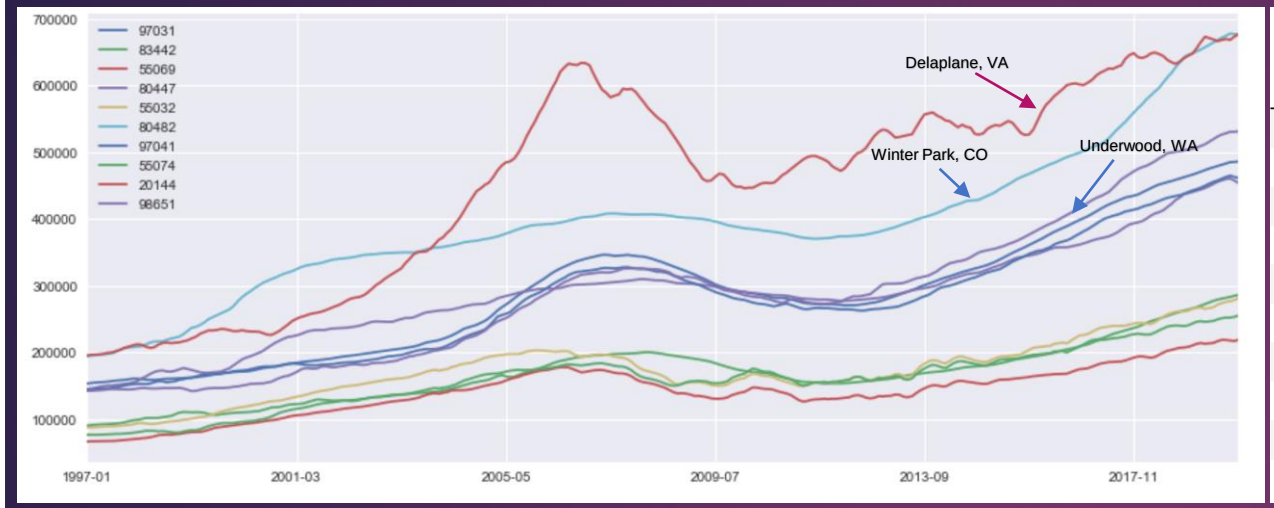
Best Zipcodes:

City	Growth	std	mean
Fayetteville	1.130409	21893.753876	179309.294444
Hot Springs	0.996877	7905.089083	123511.337500
Little Rock	0.638650	7509.868394	170605.392308
Searcy	0.557487	7454.500756	95253.145833



Exploratory Data Analysis

Top 10 Zip Codes from the final data frame after merging all the data sorting from the highest growth rate.



Best 10 Zipcodes:

	RegionName	Metro	CountyName	City	State	Growth	std	mean
28245	98651	Portland-Vancouver-Hillsboro	Skamania County	Underwood	WA	2.744479	86548.903408	372800.925000
27363	80482	NaN	Grand County	Winter Park	CO	2.490861	98718.041136	470620.433333
20006	20144	Washington-Arlington-Alexandria	Fauquier County	Delaplane	VA	2.468982	68402.012014	558770.791667
21239	55074	Minneapolis-St. Paul-Bloomington	Chisago County	Shafer	MN	2.353474	31500.079045	193209.441667
21237	55069	Minneapolis-St. Paul-Bloomington	Chisago County	Rush City	MN	2.310456	28099.555029	163006.958333
17861	97041	Hood River	Hood River County	Mount Hood Parkdale	OR	2.230471	68928.748286	338221.266667
21238	55032	Minneapolis-St. Paul-Bloomington	Chisago County	Harris	MN	2.214750	40093.706509	201372.283333
19144	83442	Idaho Falls	Jefferson County	Rigby	ID	2.179051	40767.972766	197067.866667
17860	97031	Hood River	Hood River County	Hood River	OR	2.175693	73846.796956	353977.675000
27362	80447	NaN	Grand County	Grand Lake	CO	2.130602	58312.946847	339919.325000

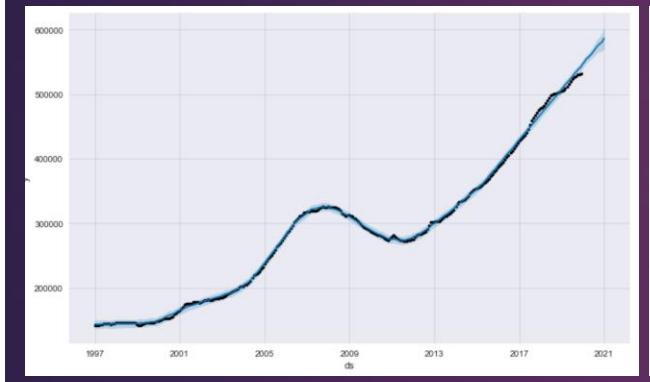
From the top 10 zip codes nationwide based on growth rates, 3 came out of Minnesota, 2 from Oregon, 2 from Colorado, 1 from Washington, 1 from Virginia, and 1 from Idaho .

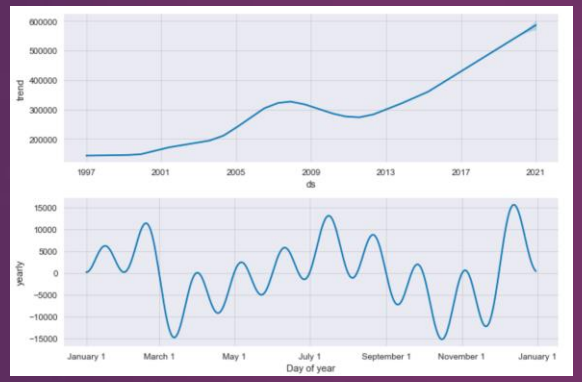
Top 3 in terms of growth rates were Underwood, WA, Winter Park, CO and Delaplane, VA, which grew by around 250% from Jan 2017 to Dec 2019.

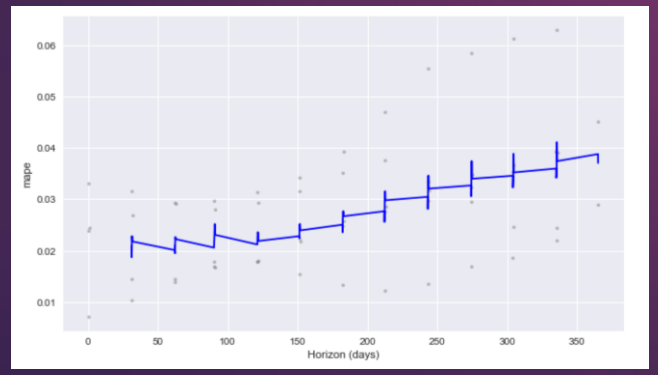
Models

Showing results from running the fbprophet of top 3 zip codes based on highest growth rates from Jan 1997 to Dec 2019. (***Note: Results from the remaining zip codes can be found from the Jupyter Notebook file.***)

Zip Code 98651 – Underwood, Washington







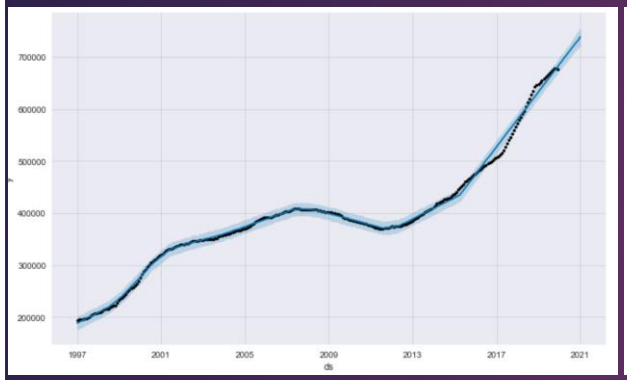
Underwood, WA has the highest growth rate of 274% from Jan 1997 to Dec 2019 with a median house value of $530K as of Dec 2019.

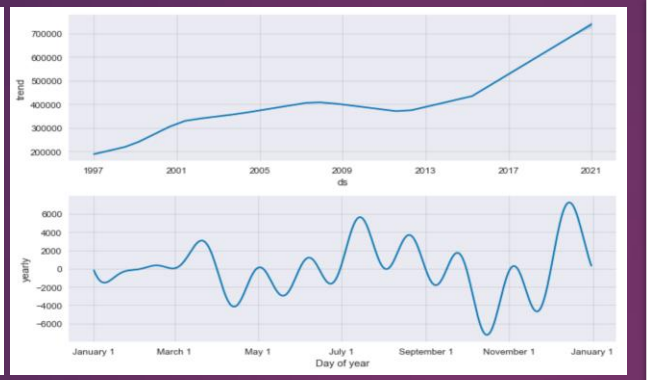
We used 12 months or 365 days as horizon in predicting performance, and 204 months prior as training data.

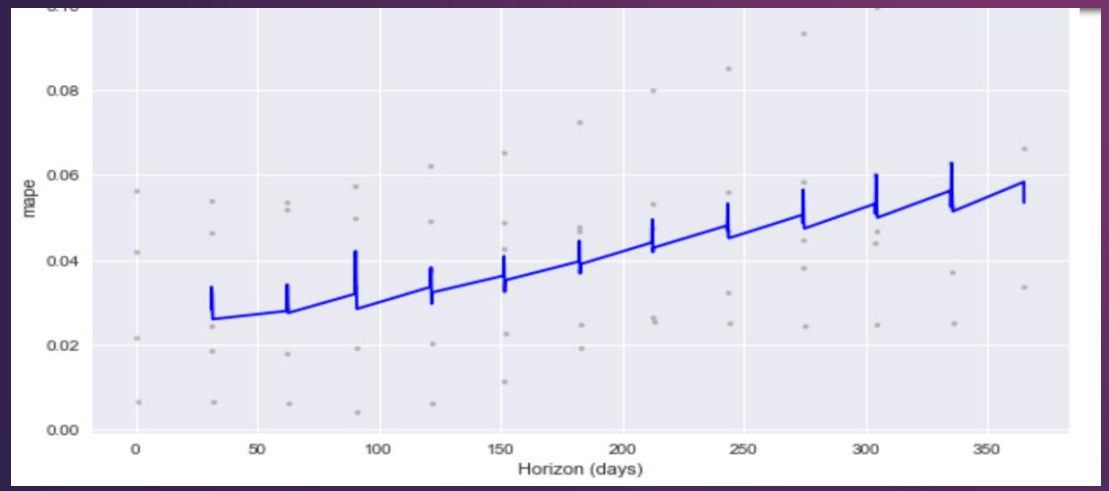
Picking on MAPE over 365 days horizon, forecast error range is from 2% to 4% (see graph).

Models

Zip Code 80482 – Winter Park, Colorado







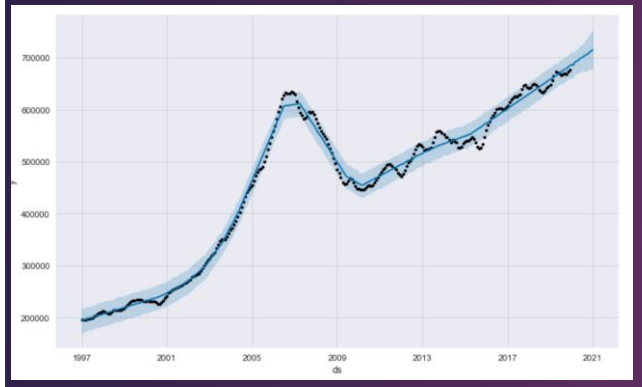
Winter Park, CO has the second highest growth rate of 249% from Jan 1997 to Dec 2019 with a median house value of $676K as of Dec 2019.

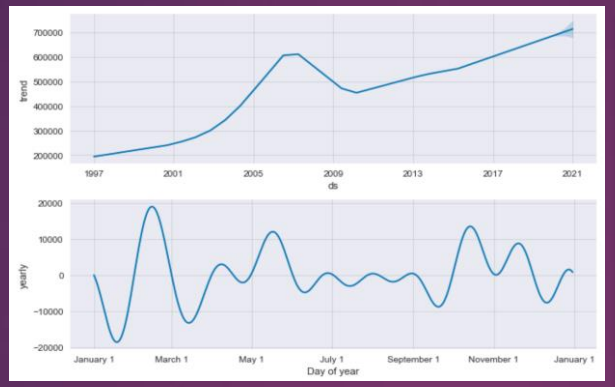
We used 12 months or 365 days as horizon in predicting performance, and 204 months prior as training data.

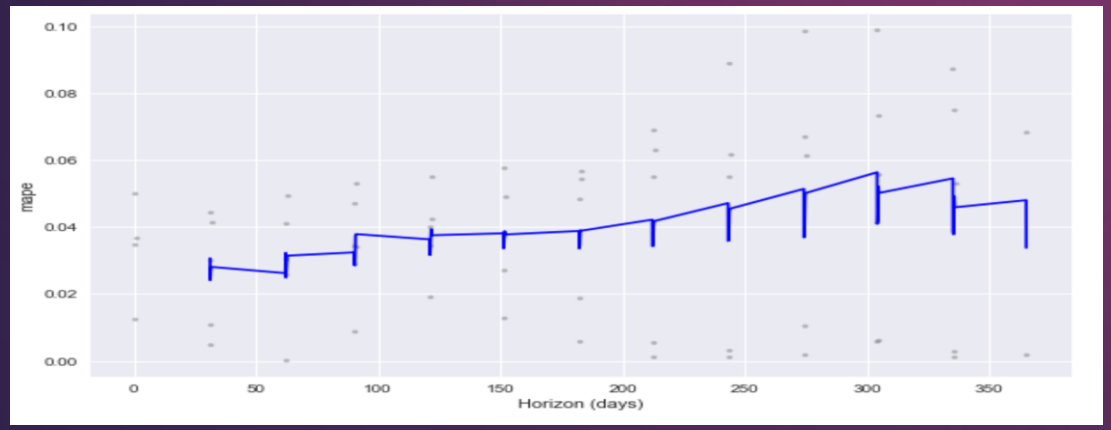
Picking on MAPE over 365 days horizon, we see that forecast error range is from 2% to 6% (see graph).

Models

Zip Code 20144 – Delaplane, Virginia







Delaplane, VA has the third highest growth rate of 247% from Jan 1997 to Dec 2019 with a median house value of $676K as of Dec 2019.

We used 12 months or 365 days as horizon in predicting performance, and 204 months prior as training data.

Picking on MAPE over 365 days horizon, we see that forecast error range is from 2% to 5% (see graph).

Models

12 Months Forecast – Y2020

	RegionID	RegionName	City	State	Metro	CountyName	SizeRank	2020-01-31 00:00:00	2020-02-29 00:00:00	2020-03-31 00:00:00	2020-04-30 00:00:00	2020-05-31 00:00:00	2020-06-30 00:00:00	2020-07-31 00:00:00	2020-08-31 00:00:00	2020-09-30 00:00:00	2020-10-31 00:00:00	2020-11-30 00:00:00	2020-12-31 00:00:00
0	99945	98651	Underwood	WA	Portland-Vancouver-Hillsboro	Skamania County	22693	550465.839292	554613.452136	556657.632906	559471.671146	562697.056226	566112.211199	570211.351249	573733.514426	576668.900097	579026.281911	581424.974755	586556.431486
1	93426	80482	Winter Park	CO	NaN	Grand County	15679	689779.459710	694135.172726	698922.658280	702956.013191	707318.989494	711743.653492	716446.360678	720876.079826	725208.074245	729089.177895	732956.831768	738574.654143
2	66240	20144	Delaplane	VA	Washington-Arlington-Alexandria	Fauquier County	21925	685138.293561	691919.380750	692702.053607	695173.754188	698467.065996	700223.813282	702630.362966	705082.883795	706304.316284	709871.948399	712540.598814	714668.616186
3	82086	55074	Shafer	MN	Minneapolis-St. Paul-Bloomington	Chisago County	18169	253644.389618	261040.599440	259784.187747	259824.632097	260611.483007	262572.080797	264362.978651	266035.283981	266586.858648	267875.250199	268627.017393	269061.847659
4	82081	55069	Rush City	MN	Minneapolis-St. Paul-Bloomington	Chisago County	13351	220876.228446	223862.517907	223666.274623	224345.992793	225507.526766	226998.445746	228521.447644	229549.912176	230176.347038	231217.449718	232398.893273	233334.415774
5	99045	97041	Mount Hood Parkdale	OR	Hood River	Hood River County	16248	477589.348369	480517.481019	482175.760356	484825.573570	487422.636823	489699.960108	492217.507002	494930.222586	497925.399060	499571.552676	501413.068684	505025.898556
6	82054	55032	Harris	MN	Minneapolis-St. Paul-Bloomington	Chisago County	15468	281124.910376	285782.638594	285653.663524	286500.297804	287871.357950	289983.973696	291640.722191	293396.941744	294355.922160	296227.402535	297371.514815	298030.419328
7	94167	83442	Rigby	ID	Idaho Falls	Jefferson County	7026	286738.623632	291583.112442	292880.659279	294462.300396	296143.176269	297874.920680	299924.480341	301740.035814	304034.004847	305957.179289	307473.471303	308678.650782
8	99035	97031	Hood River	OR	Hood River	Hood River County	6089	503689.527147	506212.603894	508566.346205	511194.249697	513880.963397	516268.432733	519214.594308	522103.506542	524838.168356	526751.249552	528414.617633	532895.092976
9	93397	80447	Grand Lake	CO	NaN	Grand County	15011	464184.261973	465433.301542	467910.507183	470317.422630	472697.810458	475298.631884	477641.467928	480002.061732	482430.410167	484356.383973	486151.065435	489527.122803

Models

Zip Code	City	State	Dec 2019 House Value	Dec 2020 House Value	Difference Bet Dec '20 and '19	Dec 2020 / Dec 2019
98651	Underwood	WA	531,379	586,556	55,177	10.4%
97031	Hood River	OR	485,881	532,895	47,014	9.7%
97041	Mount Hood Parkdale	OR	461,224	505,026	43,802	9.5%
80482	Winter Park	CO	676,089	738,575	62,486	9.2%
83442	Rigby	ID	285,927	308,679	22,752	8.0%
80447	Grand Lake	CO	453,762	489,527	35,765	7.9%
55069	Rush City	MN	218,596	233,334	14,738	6.7%
55032	Harris	MN	280,712	298,030	17,318	6.2%
20144	Delaplane	VA	676,899	714,669	37,770	5.6%
55074	Shafer	MN	255,025	269,062	14,037	5.5%

Growth rates from Dec 2019 to Dec 2020 highlighting the initially chosen Top 3 zip codes.

Conclusion

Zip Code	City	State	Growth	STD	MEAN	MAPE	Dec 2019 House Value	Dec 2020 House Value	Difference Bet Dec '20 and '19	Dec 2020 / Dec 2019
98651	Underwood	WA	274%	86,549	372,801	2% - 4%	531,379	586,556	55,177	10.4%
80482	Winter Park	CO	249%	98,718	470,620	2% - 6%	676,089	738,575	62,486	9.2%
20144	Delaplane	VA	247%	68,402	558,771	2% - 5%	676,899	714,669	37,770	5.6%
55074	Shafer	MN	235%	31,500	193,209	1.5% - 3.5%	255,025	269,062	14,037	5.5%
55069	Rush City	MN	231%	28,100	163,007	1.5% - 3.5%	218,596	233,334	14,738	6.7%
97041	Mount Hood Parkdale	OR	223%	68,929	338,221	2% - 5%	461,224	505,026	43,802	9.5%
55032	Harris	MN	221%	40,094	201,372	1.5% - 3.5%	280,712	298,030	17,318	6.2%
83442	Rigby	ID	218%	40,768	197,068	3% - 5%	285,927	308,679	22,752	8.0%
97031	Hood River	OR	218%	73,847	353,978	2% - 4%	485,881	532,895	47,014	9.7%
80447	Grand Lake	CO	213%	58,313	339,919	2% - 4%	453,762	489,527	35,765	7.9%

Using fbprophet as forecasting algorithm helped us use the outputs in determining the forecast in the next 12 months of Y2020.

Main considerations were growth rates from Dec 2019 to Dec 2020, absolute change or increase in value and MAPE.

The final Top 3 zip codes recommended were 98651-Underwood, WA, 80482-Winter Park, CO and 97031-Hood River, OR.

The combined growth rate from Dec 2019 to Dec 2020 was estimated to be around 9.75% and absolute change or increase of $165K in a 12-month period. In short, investing a total of $1,693K as of Dec 2019 median home value for the 3 zip codes was forecasted to be $1,858K by Dec 2020.

Recommendations

In the interest of time in getting more data or information, these analyses were scoped down to only using crime rates and median household income in filtering the data.

Information like economic growth rates, unemployment rate, infrastructure development scoring, and investment scoring can be used.

Moreover, recommending the Top 3 zip codes also depends on the available resources as a consideration that wasn't provided for this case study.

Inbound Crossing at the US-Canada and US-Mexico Border

Motivation

- The main goal of this project is to provide insight on some questions in relation to people crossing the US-Canada and US-Mexico border from years 1996 to 2018.
- The idea is to present a poster using Adobe Illustrator that can walk through readers some questions showing through visual communication.
- Moreover, some readers are drawn to paying more close attention to colors, maps, graphs, and some facts which the poster which reflect on.
- The output can also be educational to students who are interested at a quick glance some facts on immigration which is one of the political highlights of the country.

Business Questions

- How many have entered the United States from the Canadian and Mexican ports from Y1996 to Y2018?
- What is the split of border crossing coming from Mexico and Canada?
- Which states do people cross from?
- What are the top 10 port of entries?
- What are the mode of entries?
- How many pedestrians have crossed the border? What is the trend?
- Which states are pedestrians crossing from?
- What are number of pedestrians crossing by port?

The Collection of Data

- The 35MB csv data was sourced from Kaggle (https://www.kaggle.com/akhilv11/border-crossing-entry-data) with 344,369 rows and 9 columns
- Read the downloaded csv file using R.

	Port.Name	State	Port.Code	Border	Date	Measure	Value	Lon	Lat
1	Van Buren	Maine	108	US-Canada Border	2018	Trucks	1204	-67.94271	47.16207
2	Maida	North Dakota	3416	US-Canada Border	2018	Trucks	170	-98.36953	48.98568
3	Douglas	Arizona	2601	US-Mexico Border	2018	Buses	210	-109.54472	31.34444
4	Presidio	Texas	2403	US-Mexico Border	2018	Bus Passengers	238	-104.37167	29.56056
5	Anacortes	Washington	3010	US-Canada Border	2018	Personal Vehicle Passengers	5350	-122.61739	48.49988
6	Brownsville	Texas	2301	US-Mexico Border	2018	Truck Containers Full	9871	-97.49722	25.90139
7	Maida	North Dakota	3416	US-Canada Border	2018	Truck Containers Empty	162	-98.36953	48.98568
8	Columbus	New Mexico	2406	US-Mexico Border	2018	Pedestrians	24168	-107.63944	31.82750
9	Eastport	Maine	103	US-Canada Border	2018	Truck Containers Empty	89	-66.99387	44.90357
10	Calais	Maine	115	US-Canada Border	2018	Trucks	4504	-67.27917	45.18889

Pre-Processing and Data Cleaning

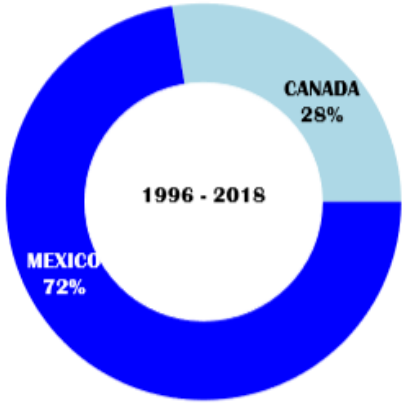
- Abbreviation state names to .
- Renamed “measures” or modes of entry.
- No NaN values were found from the dataset.

Exploratory Plots

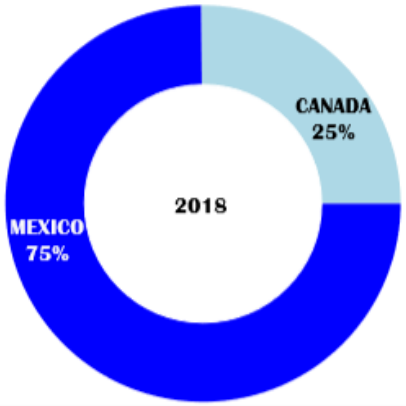
Entries in the United States from Y1996 to Y2018.

QUESTION #2: What is the split of border crossing coming from Mexico and Canada?

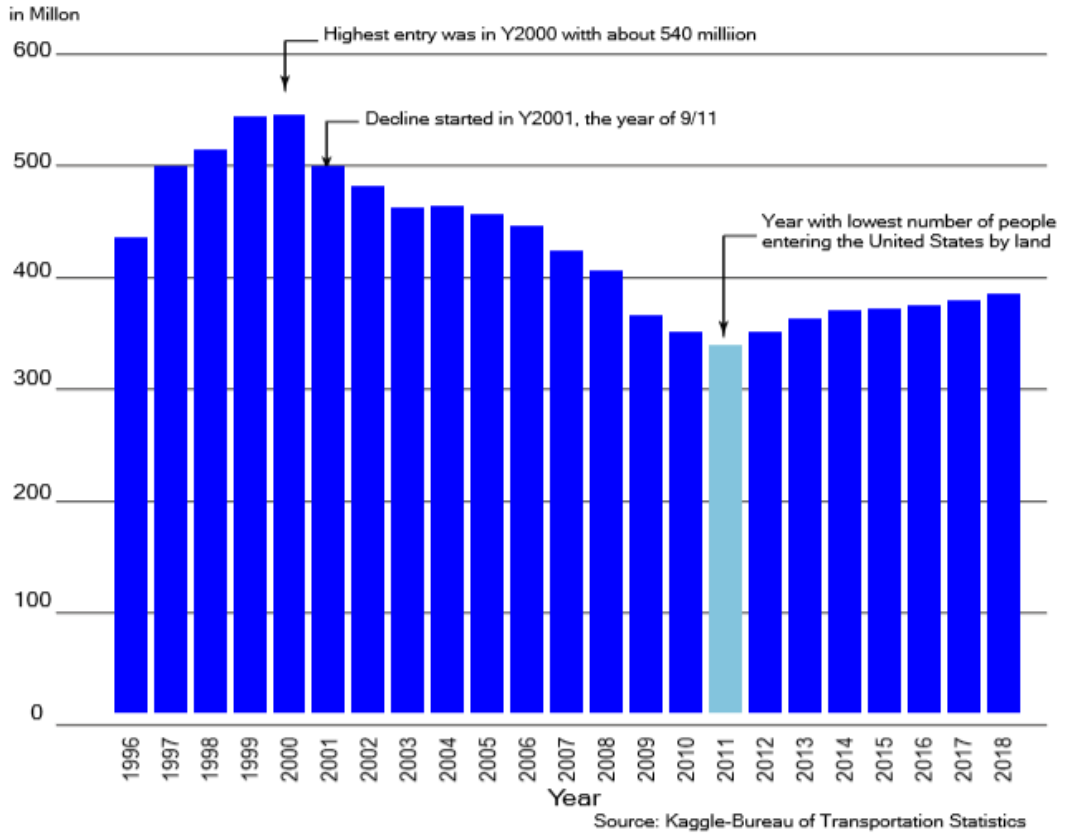
From 1996 to 2008, 72% and 28% crossed through Mexico and Canada, respectively.



In 2018 alone, the split changed in favor of Mexico now at 75%. The % split started to change ito 75% in 2017.



QUESTION #1: How many have entered the United States from the Canadian and Mexican ports from Y1996 to Y2018?



Exploratory Plots

US States where people cross into.

QUESTION #3: Which states do people cross from?

Inbound Crosssing from Y1996 to Y2018
Canada to US and Mexico to US

Number of Entries for the Past 12 Year

NY is the state with the highest reported number of entries from Canada.

TX is the state with the highest reported number of entries from Mexico.

Source: Kaggle-Bureau of Transportation Statistics

Top 5 States where poeple enter from:

1. Texas (US - Mexico border)
2. California (US - Mexico border)
3. Arizona (US - Mexico border
4. New York (US - Canada border)
5. Michigan (US - Canada border

.

Exploratory Plots

Top 10 port of entries.

QUESTION #4: What are the top 10 port of entries?

Port of Entry Definition:
It is where one may lawfully enter a country. It has border security staff and facilities to check passports and visas. US has 328 ports of entry. .

Top 10 ports of entry haven't changed when comparing combined data from years 1996 to 2018 to year 2018 alone.

El Paso in Texas ranked the highest in terms of entries from years 1996 to 2018.

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El Paso in Texas is a city and the county seat of El Paso County.

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San Ysidro in California ranked the highest number of entries for year 2018 alone.

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San Ysidro in California is a district of the City of San Diego.

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- 4 ports from Texas
- 3 ports from California
- 1 port from New York
- 1 port from Arizona
- 1 port from Michigan

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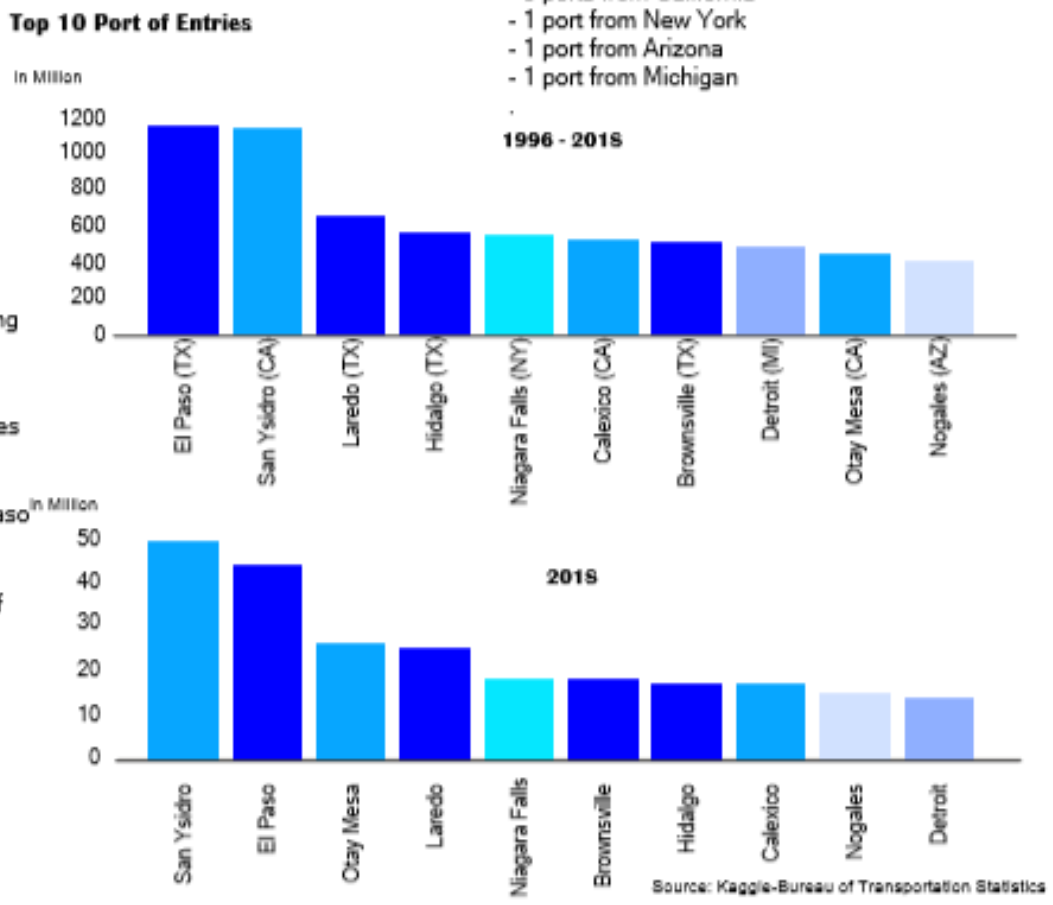
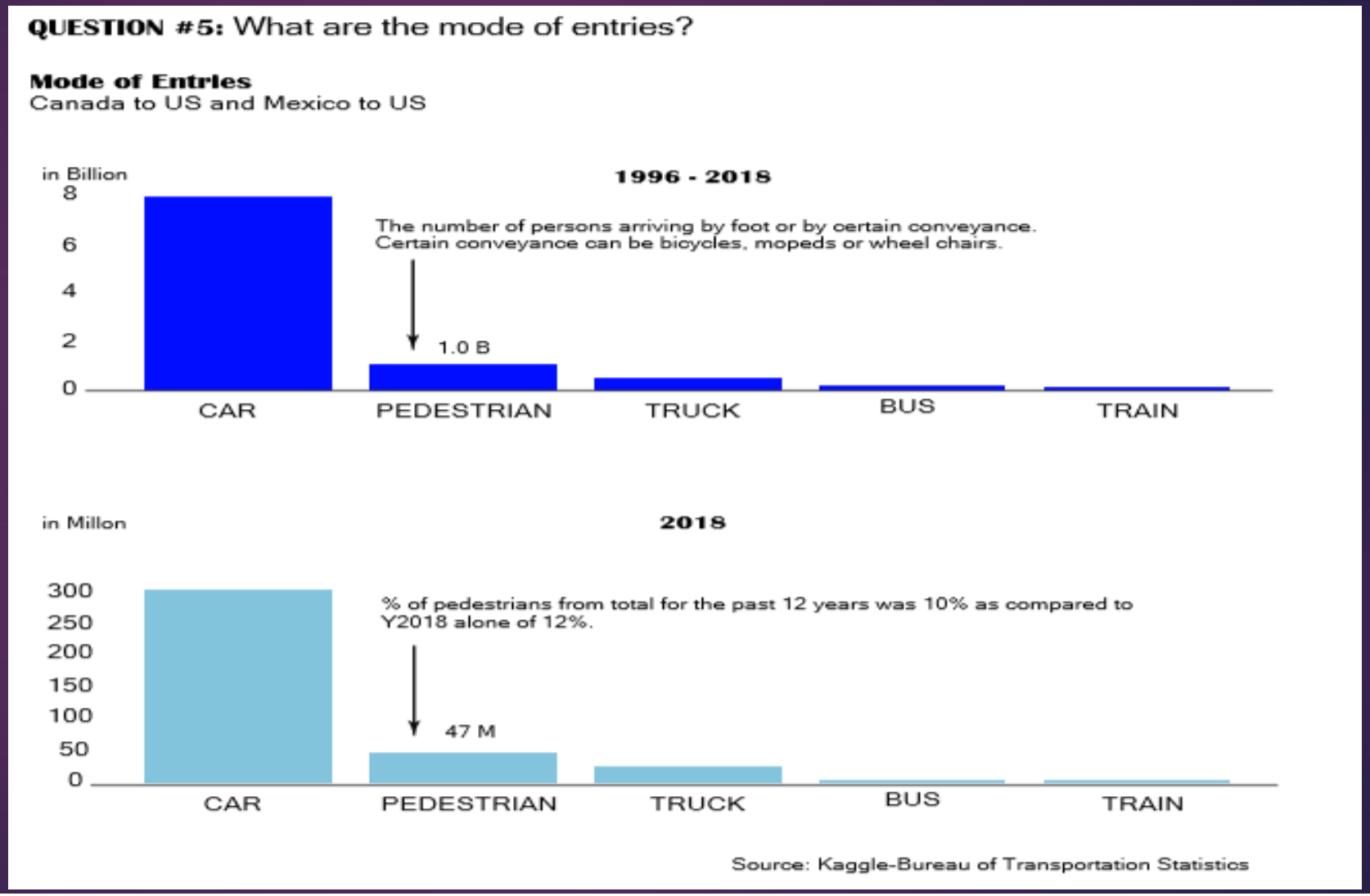


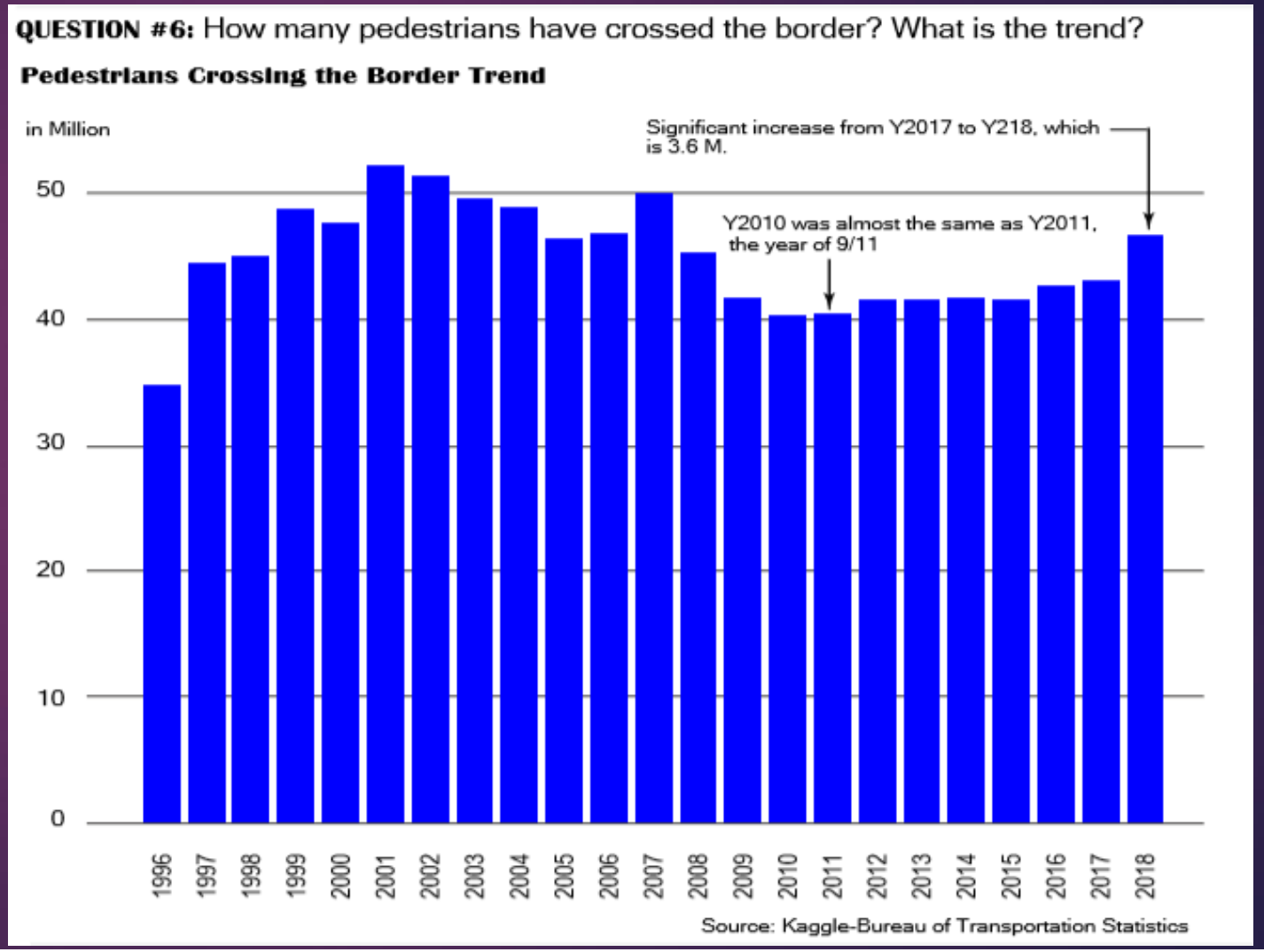
Exploratory Plots

Mode of entries



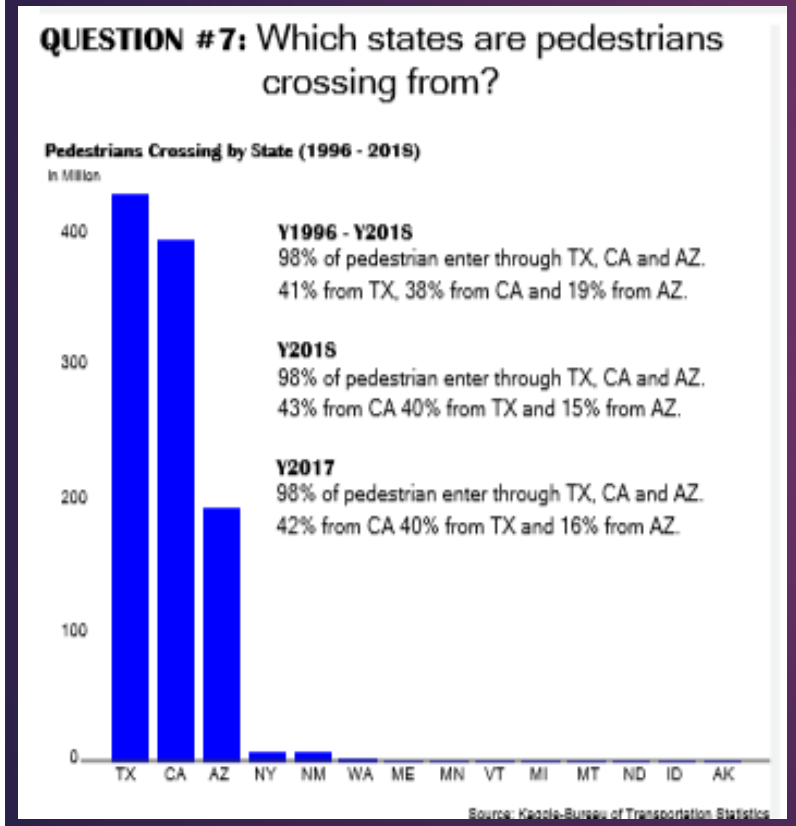
Exploratory Plots

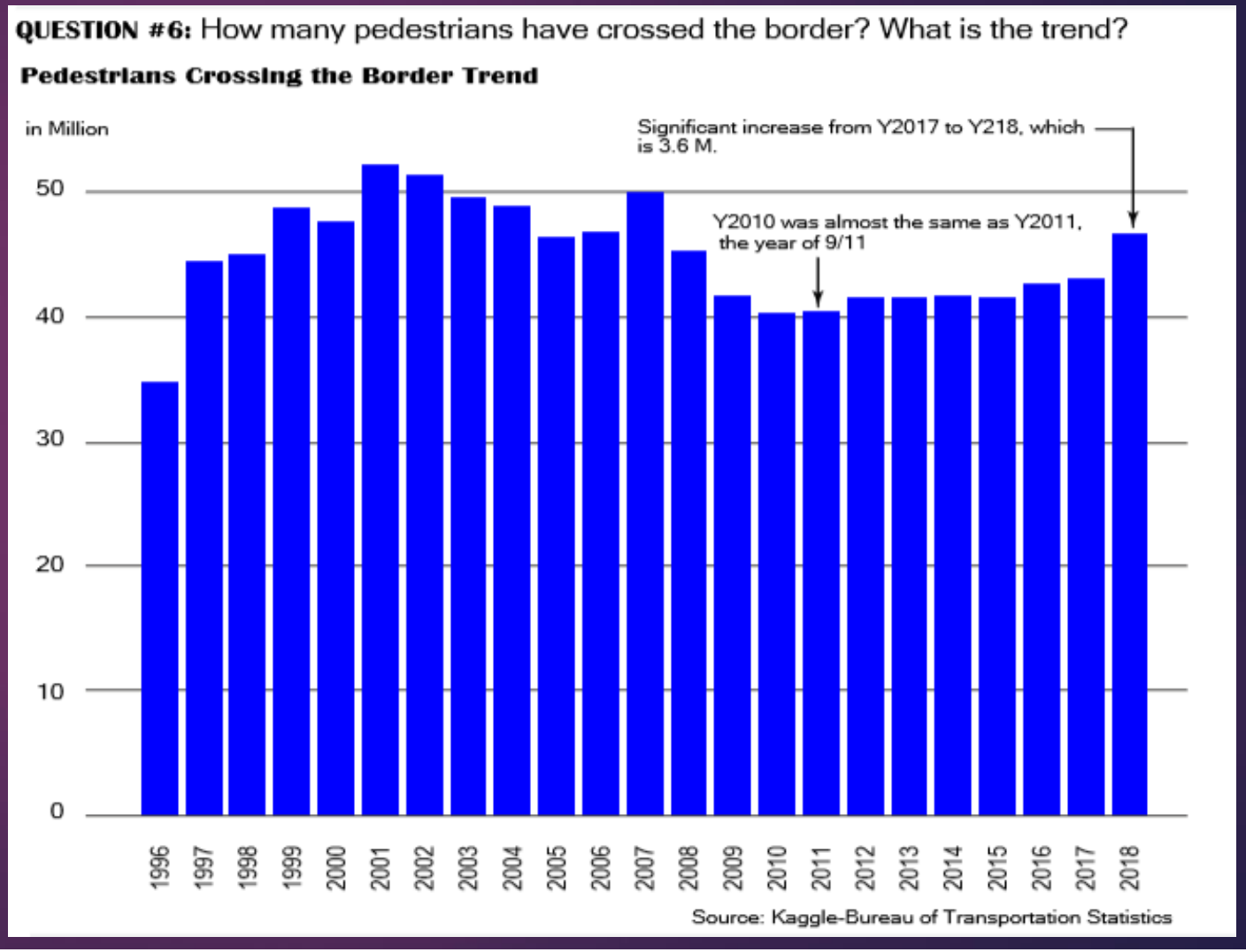
Number of pedestrians crossing the border.



Exploratory Plots

Number of pedestrians crossing the border.





Final Poster

INBOUND CROSSING AT THE US-CANADA AND US-MEXICO BORDER
Y1996 to Y2018

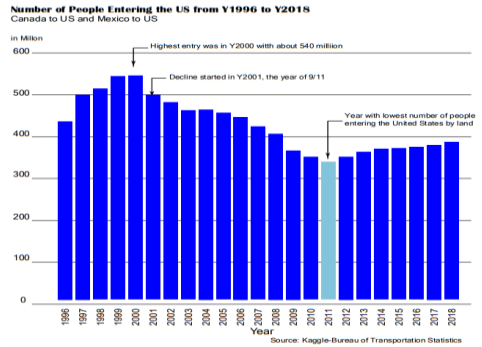
Student: Allan Flores
Course: IST719
Prof: Gary Krudys

INTRODUCTION: Sereral arguments and exchange of thoughts and ideas have circled around immigration and more so in recent years. Data depicted from this survey is an outlook of people entering the United States from Mexico and Canada by land.

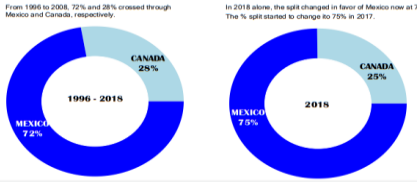
MOTIVATION: Understand through data how people enter the United States by land coming from Mexican and Canadian borders. Has there been any decline in the number of entries over time ? Moreover, answer some questions as regards to immigration given the questions going around.

DATA DESCRIPTION: Data has around 350K observations and 9 variables sourced from Kaggle. Data covered was from year 1996 to 2018.

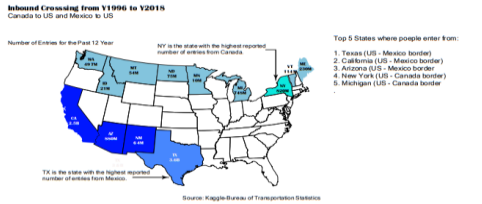
QUESTION #1: How many have entered the United States from the Canadian and Mexican ports from Y1996 to Y2018?



QUESTION #2: What is the split of border crossing coming from Mexico and Canada?



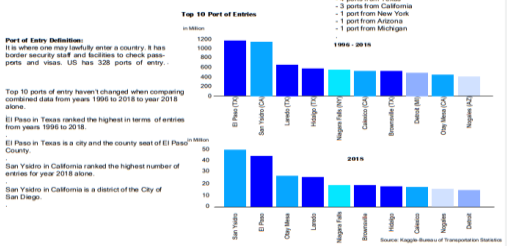
QUESTION #3: Which states do people cross from?



Top 5 States where people enter from:

1. Texas (US - Mexico border)
2. California (US - Mexico border)
3. Arizona (US - Mexico border
4. New York (US - Canada border)
5. Michigan (US - Canada border

QUESTION #4: What are the top 10 port of entries?



- 4 ports from Texas
- 3 ports from California
- 1 port from New York
- 1 port from Arizona
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Port of Entry Definition:
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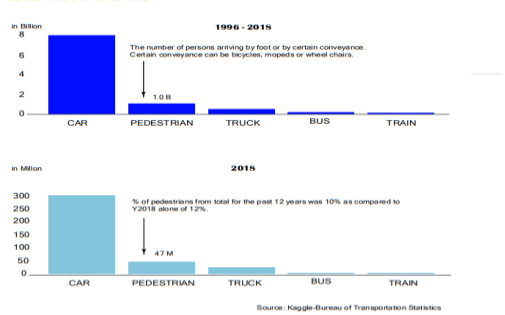
El Paso in Texas is a city and the county seat of El Paso County.

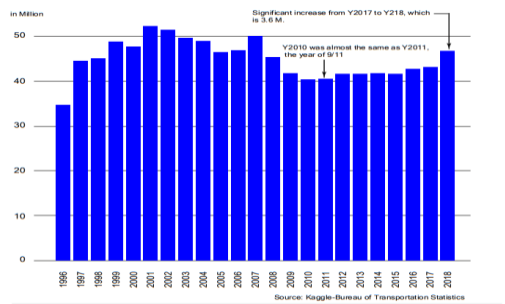
San Ysidro in California ranked the highest number of entries for year 2018 alone.

San Ysidro in California is a district of the City of San Diego.

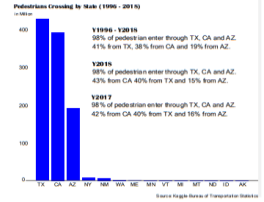
QUESTION #5: What are the mode of entries?



QUESTION #6: How many pedestrians have crossed the border? What is the trend?



QUESTION #7: Which states are pedestrians crossing from?

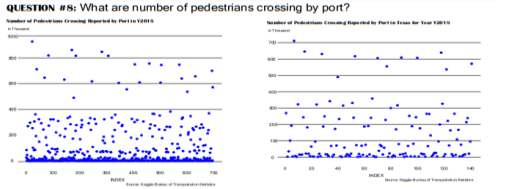


SOME FACTS ABOUT IMMIGRATION:

1. United States has more immigrants than any country in the world.
2. As of Y2019, 40 million people living in the U.S. were born in another country, which is one-fifth of the world's migrants in Y2017.
3. Population of immigrants is very diverse, with about every country in the world is represented amonth U.S. immigrants.
4. Immigrants today account for 13.6% of the U.S. population, nearly triple the share in Y1970 (4.7%).
5. However, today's immigrant share remains below the record 14.8% share in Y1890, when 9.2 million immigrants lived in the U.S.
6. Most immigrants (77%) are in the country legally, while almost a quarter unauthorized.
7. Mexico is the top origin country of the U.S. immigrant population.
8. In Y2017, 25% of immigrants were from Mexico.
9. The next largest origin groups were from China (6%), Indian (6%), the Philippines (5%) and El Salvador (3%).
10. By region of birth, immigrants from South and East Asia combined accounted for 27% of all immigrants.

Source: Pew Research Center

QUESTION #8: What are number of pedestrians crossing by port?



Thank You!