Forecasting Avocado Prices

Avocado King can use data to optimize profits

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The problem

Company	Context	Problem statement
Avocado King , a major distributor of avocados across the USA	Avocado **prices fluctuate** based on a variety of factors Avocado King stores historical **sales and price data** Google provides historical **search data**	There is a need to **forecast avocado prices** to enable company-wide financial planning

Challenges deep-dive

Understand data

Through data visualization, we can better **see relationships** in the data and develop analytical approach

Prepare data

The data given has a unique key: **[date, region, type]**

- Data must be **cleaned** and **normalized** carefully with key in mind

Model prices

Utilize sound statistical analyses and **machine learning** to model prices

- Random forest regression
- Linear regression

Solution

Linear Regression

On average, the selected model predicts avocado prices **within 11 cents of the true value**.

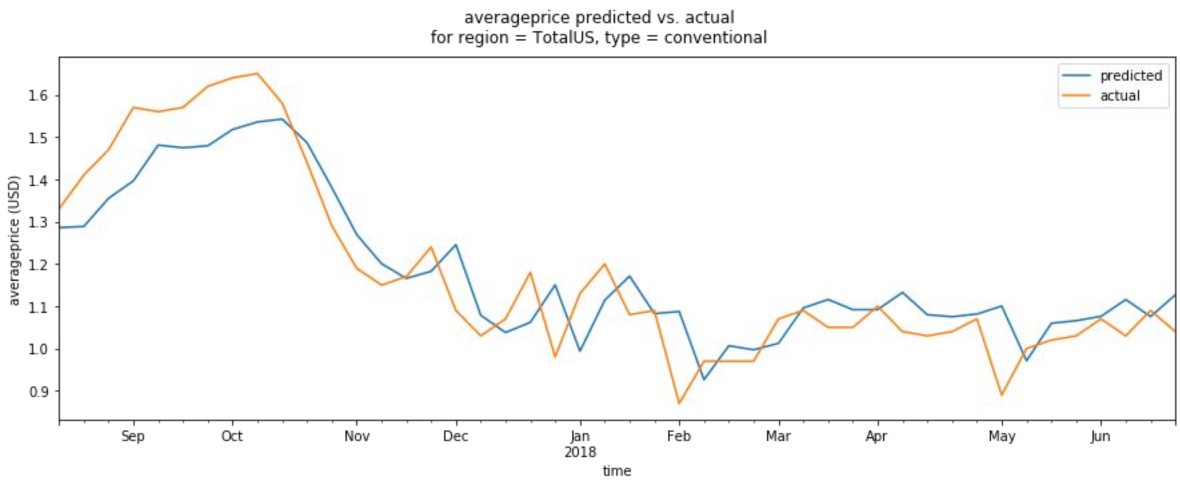
Forecasting 1 week ahead
Mean absolute error = 0.11

84%

of variation seen in price is explained by the selected model

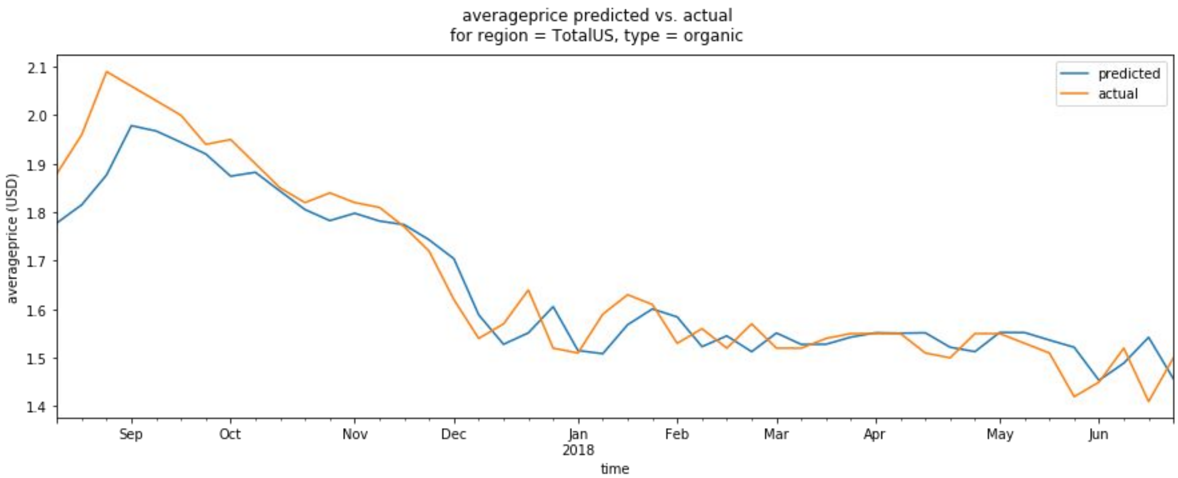
R-squared = 83.72% (coefficient of determination)

Model performance



Validation set

Model performance



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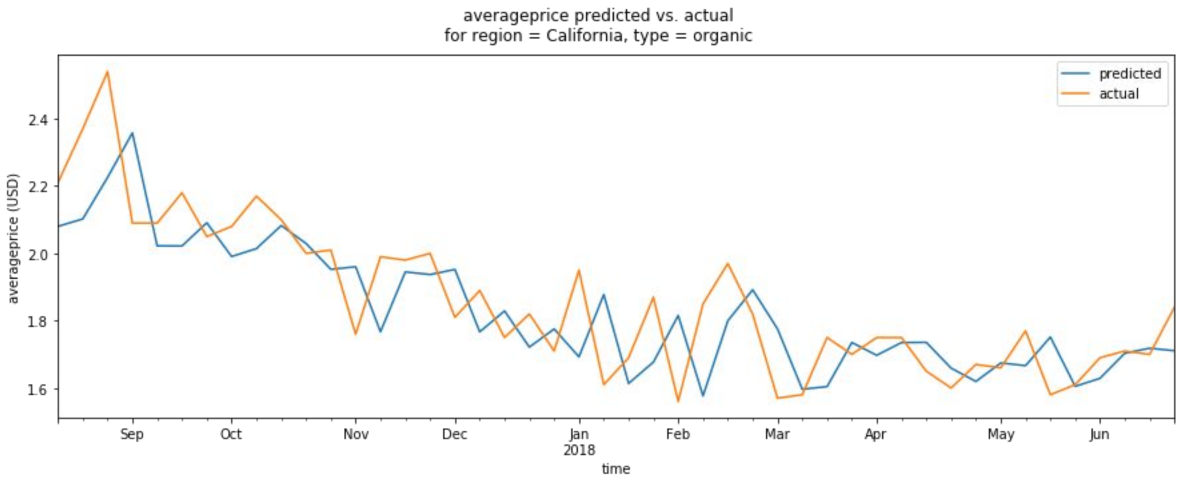

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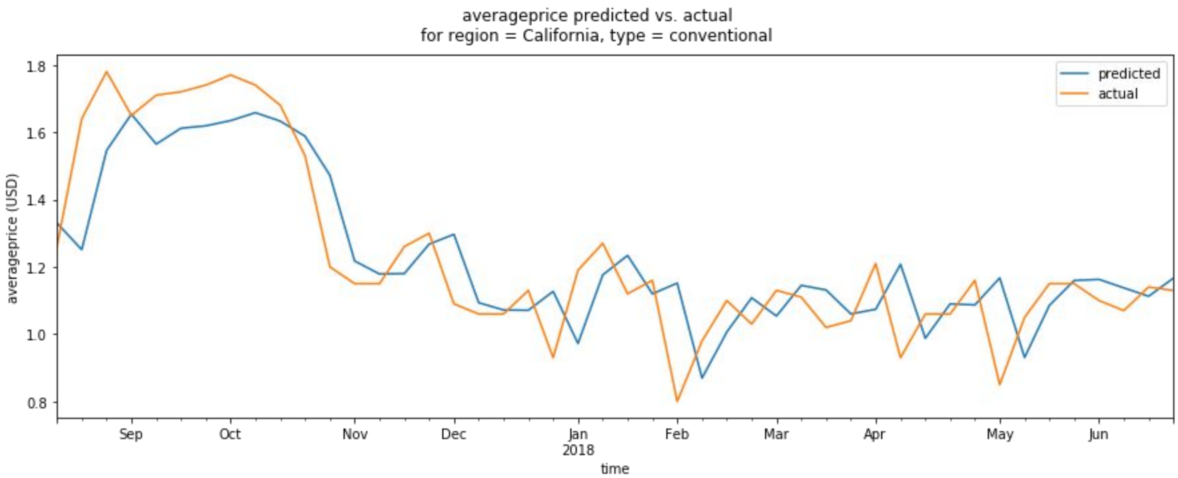

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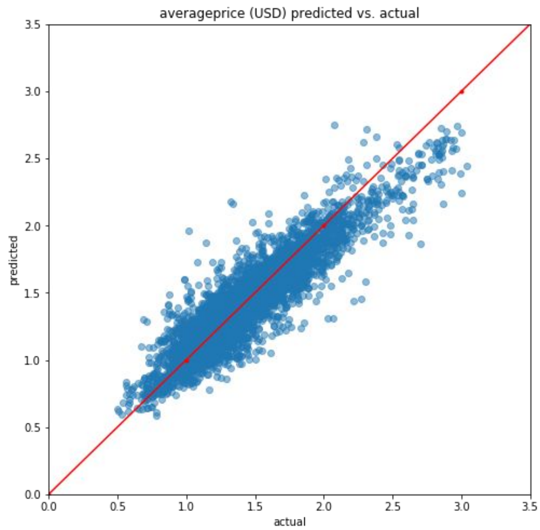
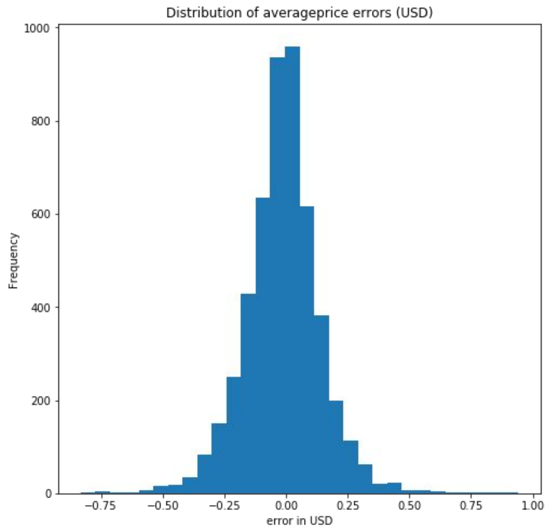


Validation set

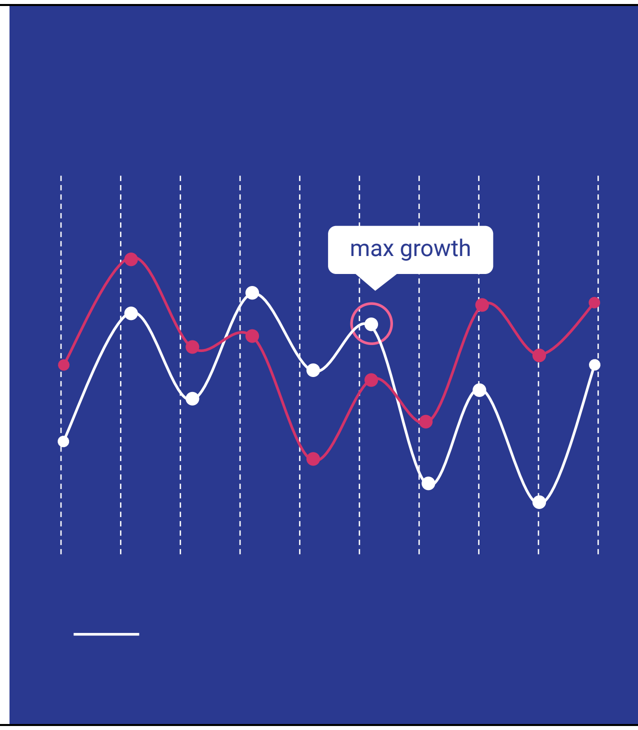
Model performance



The errors are approximately normally distributed, meaning the model is low in bias.
Validation set

Impact

Forecast prices => **Plan ahead**
=> **Optimize profits**
=> **Maximize growth**



Next steps

This proof of concept can be expanded upon:

- Higher accuracy
- Forecasting weekly, monthly, quarterly, yearly
- Forecasting volume sold

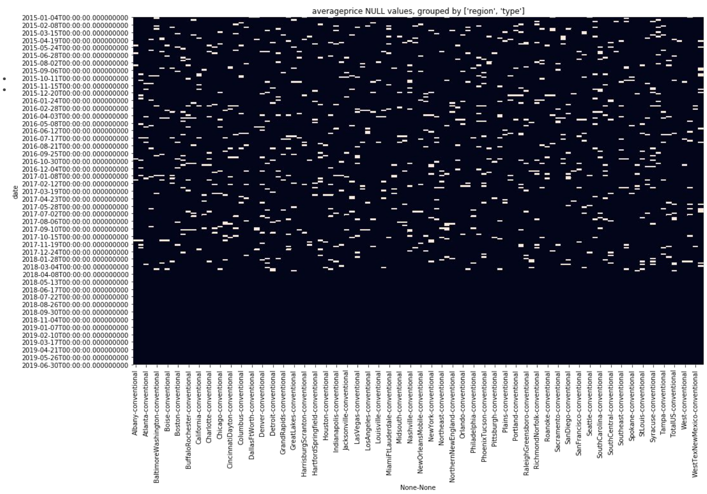
Technical details

Data cleaning

There is a unique key for this dataset: [date, region, type]. We ensured no data was missing:

1. Check for **extra dates** (out of expected weekly sequence)
2. Check for **missing dates** (based on expected weekly sequence)
3. Use **forwardfill** to fill nulls
4. Use **backwardfill** to fill remaining nulls

Each unique key combination was visualized:

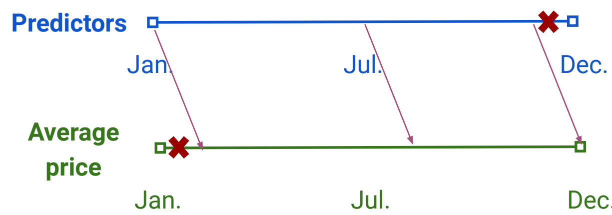


Technical details

Time shifting

In forecasting, we use values from this week predict next week's values. So we shifted the data accordingly.

1. Drop the latest date in x
   a. (since it doesn't have an associated future y at *t*+1)
2. Add 7 days to each date in x
3. Drop the earliest date in y
   a. (since it doesn't have a corresponding past x at *t*-1)
4. Join the x (*t*-1) and y (*t*) dfs on the unique key [date, region, type]

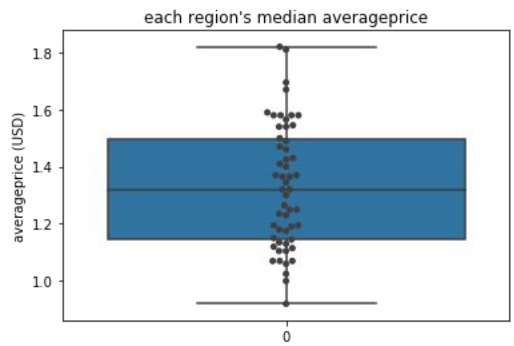


Technical details

The data

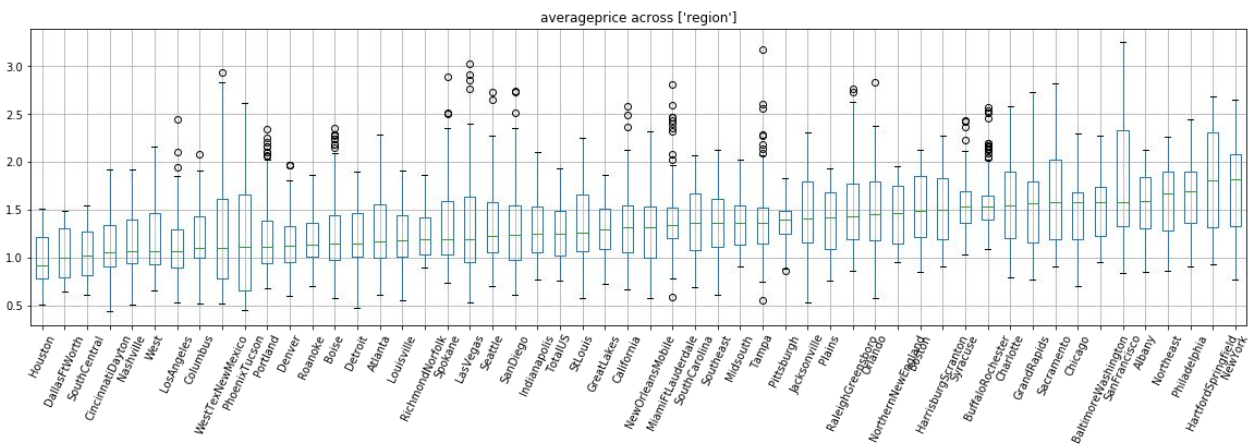
All predictive variables were shifted 1 week back to enable forecasting 1 week ahead.

- Average price (per avocado, USD)
- Region group
- Total volume (avocados sold)
- Total bags (bags sold)
- “Avocado recipe” (google search)
- Season (spring, summer, fall, winter)
- Type (conventional, organic)



- **Average_price** was included because at time *t*-1, it correlates strongly (r = 0.6) with average_price at time *t*
- **Region_group** was created to reduce the number of features in the model (reduce overfitting) while preserving the important relationship between geography and price.
- **Total_volume**, **total_bags**, and **“avocado recipe”** (google search) were chosen because when grouped by region_group, they correlated weakly (r = 0.2) to moderately (r = 0.5) with average_price.
- **Season** was added because avocados from Mexico come in season in the fall and winter. 70% of avocados sold in the USA are sourced from Mexico.
- **Type** was important to include because in the exploratory visualizations, organic can be seen as almost always more expensive

Technical details

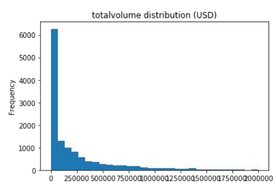


Technical details

Normalization

All numeric predictive variables were **tested** via several normalization methods, seeking to best preserve the original distribution

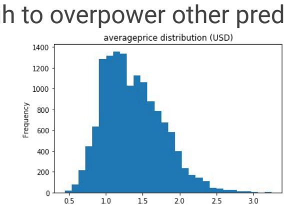
- Z-score
- Methods for preserving skewed distributions (e.g. Pareto):
    - MinMax
    - Log + MinMax
    - Cube Root + MinMax



Z-score normalized:

- Total volume
- Total bags
- “Avocado recipe” (google search)

Left average price on its original scale to preserve distribution. Original was scale not big enough to overpower other predictors.



- MinMax Normalization seems to preserve the shape of the normally distributed data best, but Z-score Standardization seems to work best in preserving the Pareto-distributed data. However using both will mean that there will be a mix of data centered at zero and data in the range [0, 1]. It is best to have all variables on the same scale. Since \`averageprice\` is the main target of interest, is normally distributed, and falls in the relatively small range [0.44, 3.25], we will leave it on its original scale and use Z-score normalization on the rest.
- Log + MinMax and Cube Root + MinMax normalization don't seem to improve over just MinMax scaling.

Technical details

Train / Validation / Test split

Since this is time series data, **we want full years (with all their seasonal variations) to exist** in the train, validation, and test set.

- training set:
  - Jan 2015 - July 2017
- validation set:
  - August 2017 - July 2018
- test set:
  - August 2018 - July 2019

→

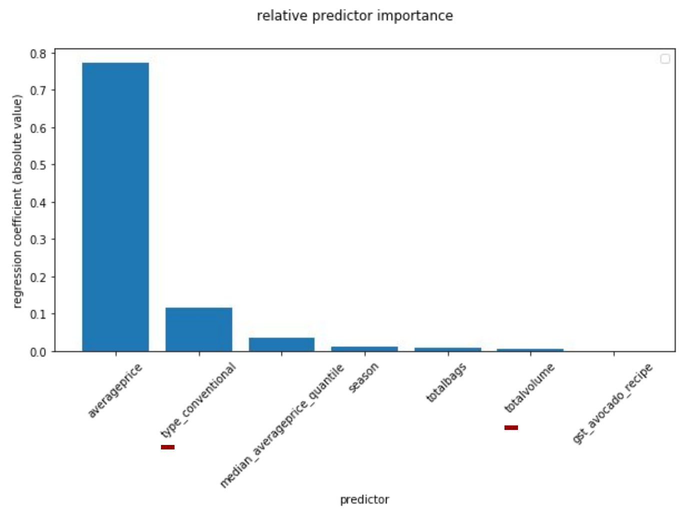
- training set:
  - 58%
- validation set:
  - 21%
- test set:
  - 21%

Technical details

Predictor importance

Based on the model, the rank of importance is:

- Average price (per avocado, USD)
- Type (conventional, organic)
- Region group (median_averageprice_quantile)
- Season (spring, summer, fall, winter)
- Total bags (bags sold)
- Total volume (avocados sold)
- "Avocado recipe" (google search)



Technical details

Error Metric

Mean absolute error was used when evaluating model performance:

- Enables us to intuitively understand how accurate our predictions will be, on average.
- MAE = 0.11
  - “On average, the model predicts avocado prices within 11 cents of the true value.”