

Fruit Pricing Across Regions and Seasons

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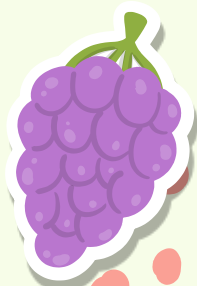
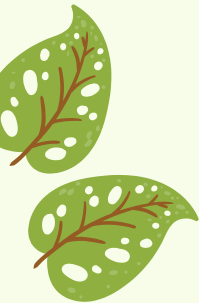
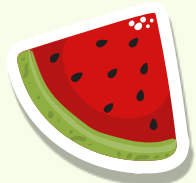
Summary of proposed actions

6

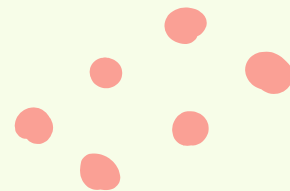
SECTION 6

Benefits of analysis





INTRODUCTION & BACKGROUND



INTRODUCTION & BACKGROUND

About Me

Amanda Yu
Alberta, Canada

Current Role

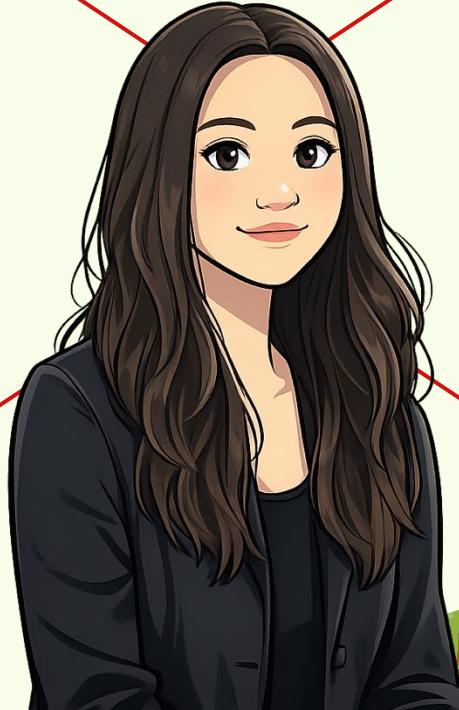
Data & Reporting
Analyst

Education

Bachelor of Commerce –
Business Analytics

Experience

Data visualization &
reporting



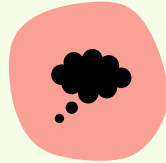


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RESEARCH QUESTION & HYPOTHESIS

RESEARCH QUESTION & HYPOTHESIS

What factors significantly influence fruit pricing across regions and seasons?



Null Hypothesis

Fruit type, region, ripeness, weight, and season have no statistically significant effect on fruit price ($p \geq 0.05$).



Alternate Hypothesis

At least one of the following variables: fruit type, region, ripeness, weight, or season have a statistically significant effect on fruit price ($p\text{-value} < 0.05$).



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SUMMARY OF ANALYSIS & FINDINGS

TOOLS AND TECHNIQUES



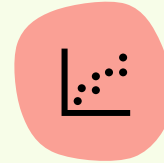
Google BigQuery

Cloud data warehouse used to store and analyze large datasets efficiently.



SQL

Query language used to retrieve, filter, and summarize data stored in relational databases.



Multiple Linear Regression

Statistical method to predict the value of one dependent variable based on two or more independent variables, and estimates how much each factor influences the outcome.

DATA ANALYSIS PROCESS



Kaggle

Dataset downloaded from open source



BigQuery

Upload dataset into tables with define schema



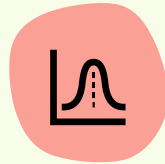
SQL

Write and save SQL queries



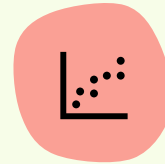
Data Quality

Check for nulls or outliers



Normality Test

Jarque-Bera test to evaluate distribution



BigQuery ML

Create linear regression model



Search BigQuery resources

Show starred only

d610-capstone-project

Repositories

Queries

Shared queries

0. jarque-bera test for normality

1. check for null values

2. check for outliers

3. data cleaning and transformation

4. create multiple linear regression models

5. evaluate model on validation set

6. get coefficients and pvalue

7. predict price per lb usd

8. create view with actual, predicted, and residuals

Notebooks

Data canvases

Data preparations

Pipelines

Connections

fruit_prices

Models (1)

fruit_prices_cleaned

fruit_prices_summary

v_actual_residual

d610-capstone-project / Datasets / fruit_prices / Tables / fruit_prices_cleaned

fruit_prices_cl...

Query

Open in

Share

Schema

Details

Table Explorer

Preview

Insights

Lineage

Data Profile

Filter Enter property name or value

<input type="checkbox"/>	Field name	Type	Mode	Description	Key	Collation	Default value
<input type="checkbox"/>	month_num	INTEGER	NULLABLE	-	-	-	-
<input type="checkbox"/>	year	INTEGER	NULLABLE	-	-	-	-
<input type="checkbox"/>	season	STRING	NULLABLE	-	-	-	-
<input type="checkbox"/>	fruit_type	STRING	NULLABLE	-	-	-	-
<input type="checkbox"/>	region	STRING	NULLABLE	-	-	-	-
<input type="checkbox"/>	state	STRING	NULLABLE	-	-	-	-
<input type="checkbox"/>	ripeness	STRING	NULLABLE	-	-	-	-
<input type="checkbox"/>	weight_lb	FLOAT	NULLABLE	-	-	-	-
<input type="checkbox"/>	price_per_lb_usd	FLOAT	NULLABLE	-	-	-	-

Edit schema

Describe data

FINDINGS



Significant Predictors

Most variables were statistically significant (19/20 $p < 0.05$, 12 with $p \approx 0$)



Model Performance

$R^2 = 0.95$ (typical error \$0.15–\$0.19/lb)



Conclusion

Reject null hypothesis because fruit type, region, ripeness, and season are significant predictors of fruit price.



Google Cloud d610-capstone-project Search (/) for resources, docs, products, and more

6. get coefficients and pvalue Run Download Save query

```
1 SELECT
2 *
3 FROM ML.ADVANCED_WEIGHTS(
4 MODEL `fruit_prices.fruit_price_linear_regression`
5 )
6 ORDER BY p_value;
7
```

Query completed

Using on-demand processing quota

Query results + Create conversation Save results Open in

Job information Results Visualization JSON Execution details Execution graph

Row	processed_input	category	weight	standard_error	p_value
1	__INTERCEPT__	null	2.301403552189...	null	null
2	fruit_type	Peach	0.0	0.0	NaN
3	region	South	0.0	0.0	NaN
4	ripeness	Slightly Unripe	0.0	0.0	NaN
5	season	Winter	0.0	0.0	NaN
6	fruit_type	Pineapple	0.650794880679...	0.008500209317...	0.0
7	fruit_type	Blueberry	2.493071186793...	0.008543439712...	0.0
8	fruit_type	Apple	-0.34238919215...	0.008549803269...	0.0
9	fruit_type	Avocado	-0.45646441618...	0.008555249301...	0.0
10	fruit_type	Strawberry	1.103273700129...	0.008556821712...	0.0
11	fruit_type	Mango	-0.73384918342...	0.008557834515...	0.0
12	fruit_type	Orange	-0.92633471095...	0.008577855681...	0.0
13	fruit_type	Banana	-1.48249184589...	0.008585782234...	0.0
14	region	West	0.207488497453...	0.005096619589...	0.0
15	region	Northeast	0.170960692000...	0.005627243142...	0.0
16	ripeness	Overripe	-0.53771043502...	0.006088357684...	0.0
17	season	Summer	-0.33481592251...	0.005447107875...	0.0
18	ripeness	Very Ripe	-0.13836849659...	0.006068530923...	1.332267629550...
19	fruit_type	Grape	0.190923115927...	0.008585792353...	1.776356839400...
20	season	Spring	-0.12093368147...	0.005435842329...	1.776356839400...
21	season	Fall	-0.09065865149...	0.005431815912...	1.718625242119...
22	ripeness	Unripe	-0.06541444045...	0.006067028427...	1.607620703225...
23	region	Midwest	0.044777373685...	0.005199561177...	5.010600157007...
24	ripeness	Ripe	0.050940803174...	0.006084887456...	7.675138080642...
25	weight_lb	null	-0.00139633364...	0.001406792514...	0.321357964099...





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LIMITATIONS OF TECHNIQUES USED

LIMITATIONS

DATASET

Dataset is synthetic and restricted to U.S. states over only two years, which limits real-world generalizability and may not reflect true market dynamics.

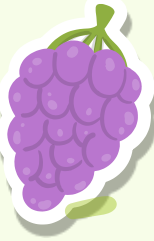


MULTIPLE LINEAR REGRESSION

Assumes straight-line relationships and may miss more complex patterns or interactions

BIG QUERY

Heavy feature engineering (like one-hot encoding) can make SQL pipelines lengthy and may increase cost if repeated queries re-scan large tables





5

SUMMARY OF PROPOSED ACTIONS

PROPOSED ACTIONS

PRICE BENCHMARKING

Use the model to estimate expected price/lb and compare pricing by fruit, region, season, ripeness, and weight.



FOCUS ON KEY DRIVERS

Track the largest and most significant coefficients to explain and anticipate price changes.



OPERATIONALIZE

In BigQuery, refresh data, retrain the model, and publish predictions to dashboards/reports.



FUTURE ENHANCEMENTS

Validate with real-world data, expand time/geography, and test interactions/nonlinear models.





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BENEFITS OF ANALYSIS

BENEFITS OF ANALYSIS



ACTIONABLE INSIGHTS

Identifies the biggest price drivers from the interpretable coefficients



ACCURATE FORECASTS

$R^2 \sim 0.95$
Typical error $\sim \$0.15 - \$0.19/\text{lb}$



SCALABLE WORKFLOW

Repeatable BigQuery ML pipeline for consistent refreshes



REFERENCES

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THANK YOU!

