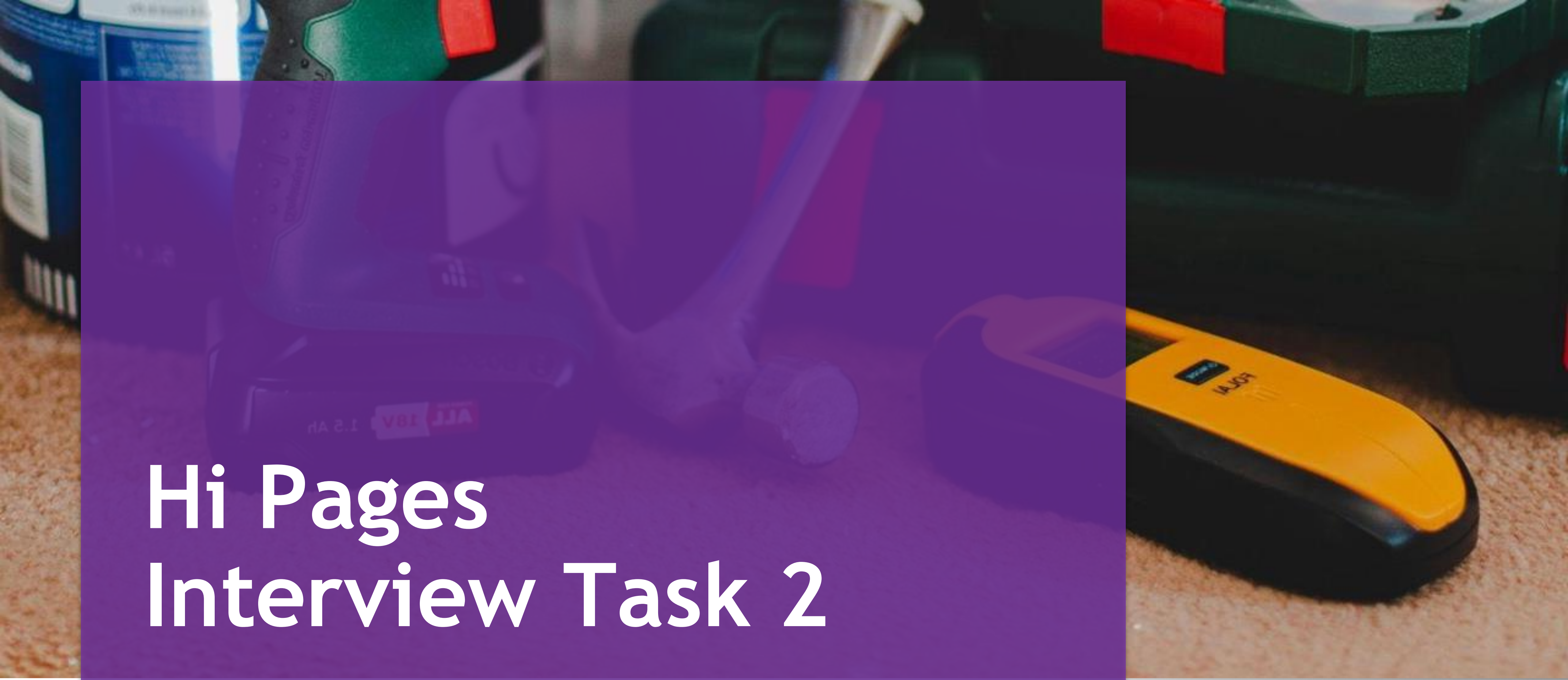


Hi Pages Interview Task 2

Exploratory Data Analysis (EDA)

February 2025

James Maulana

Recap

Executive summary

Situation

- New feature update for job tracking has been live for several weeks, and various initiatives have been deployed to **drive acceptance**. Hi Pages is looking for an update to uncover patterns and **validate progress toward acceptance targets**

Results

- **Darwin's acceptance rate** (34%) significantly **exceeds** those in **Sydney** (25%) and **Melbourne** (27%), even with fewer jobs, indicating strong regional differences
- **Acceptance peaks after lunch**, while **job postings occur primarily at midday**, suggesting a timing misalignment that may affect acceptance
- **Category-level performance varies significantly**, with certain job types consistently outperforming others both in terms of volume posted and acceptance
- Despite these results, the **most significant contributor to job acceptance** is **job size**, followed by the **number of tradies**

Next steps

- **Launching pilot initiatives in Sydney and Melbourne that mimic Darwin's best practices**, including localised marketing campaigns and incentives to boost tradie availability could improve acceptance for these cities
- **Adjusting job posting and notification schedules to focus on peak acceptance windows** (after mid-day) and to test targeted promotions during off-peak periods could smooth out acceptance rates
- **Focusing on high-performing job categories and exploring adjustments** (e.g., pricing or matching improvements) **in lower-performing categories** could further help improve acceptance rates, **while continuing to refine our predictive model** by incorporating additional factors (such as job urgency or tradie specialisation) could further guide strategic decision-making

The task

Scenario

The tracking has gone live for some time now, with a range of activities having been deployed with the objective of achieving the goal. The team would like for you to have a look at the jobs data again and use exploratory data analysis techniques.

Requirement

Analyse the data provided and present insights and recommendations. The dataset is designed to see how you approach an analytical task. You can use any approach as you see fit. Some possible scenarios that you could explore in your EDA could include:

- What data preparation steps will you implement?
- Which parameters influence if a job would be accepted?
- Can we predict using the data we have if a job would be accepted? If yes, how? If no, why not?
- Which visualisations would best communicate the findings?

Please share visualisations via Tableau Public, and use GitHub/GitLab for everything else

Resources

- **GitHub:** https://github.com/jmaulana0/Hi-Pages

Includes:

- **BigQuery** for data ingestion and manipulation
- **Python** for analysis

Methodology

Step 1: Data Collection & Preparation
Collect job posting data (including time, location, category, number of tradies, estimated size, impressions, and acceptance) and clean it using Python and pandas—convert categorical values (e.g., “small,” “medium,” “large”) into numeric codes, handle missing values, and ensure proper data types.

Step 2: Exploratory Data Analysis (EDA)
Use Python’s Seaborn and matplotlib to visualize the overall distribution of job acceptance (via count plots) and compare key parameters between accepted and non-accepted jobs with grouped bar charts and box plots.

Step 3: Statistical Testing
Apply two-sample t-tests (using scipy.stats) to quantitatively compare means of parameters (like the number of tradies) between accepted and not accepted groups, confirming whether observed differences are statistically significant (p-value < 0.05).

Step 4: Predictive Modeling
Develop a logistic regression model using scikit-learn to predict job acceptance based on key features, and analyze model coefficients to understand the direction and magnitude of influence; for detailed inference with p-values, use Statsmodels’ Logit function.

Step 5: Synthesis & Recommendations
Integrate insights from the visual analysis, statistical tests, and predictive modeling to pinpoint the most influential parameters, then formulate actionable strategies—such as optimizing tradie recruitment or adjusting marketing—to improve job acceptance rates.

Acceptance deep dive

4.

Acceptance rates are driven by four broad categories

Regional Performance

- Darwin shows a higher acceptance rate (34%) despite having fewer total jobs compared to Sydney (24.8%) and Melbourne (27.2%)
- Geographic clustering (via DBSCAN) confirms statistically significant differences between regions (ANOVA p-value < 0.0001)

Time & Scheduling

- Clear pattern in acceptance rate peaking after lunch; no clear pattern is observed by day of the week
- Job postings most frequent around midday, suggesting that homeowners are most active during that period
- Additional peak in job size at night that align with increased acceptance rates

Job Category Performance

- Some job categories (for example, categories 3 and 6) consistently show higher candidate engagement and acceptance rates
- Average impressions and job size are fairly uniform across categories, suggesting that listing behavior is consistent, but acceptance may be driven by other category-specific factors

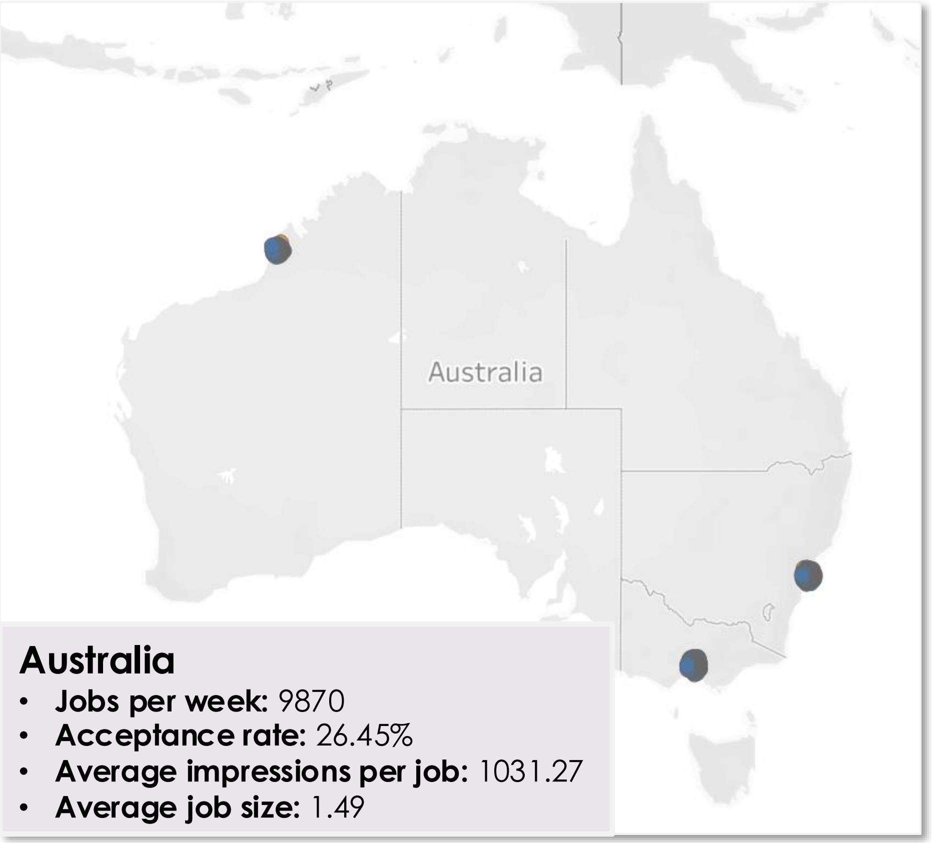
Model Insights & Key Predictors

- The logistic regression model (pseudo R^2 ~9.5%) shows that estimated job size is the largest predictor, with a significant positive impact on acceptance
- Number of tradies has a statistically significant (though smaller) positive effect
- Categories and City clustering variations do not help predict for acceptance

Source: Scoop.market.us
Note: 1. Non-Chinese used as US and other markets considered closer comparison to Australian potential trajectory

Darwin offers higher job acceptance rate compared to Sydney and Melbourne despite smaller size and fewer jobs

Operate across Darwin, Melbourne, and Sydney



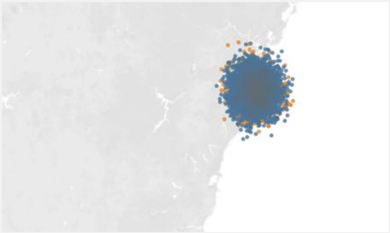
Australia

- **Jobs per week:** 9870
- **Acceptance rate:** 26.45%
- **Average impressions per job:** 1031.27
- **Average job size:** 1.49

Insight

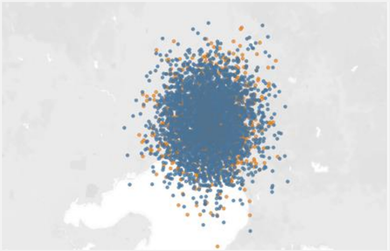
Sydney

- **Total jobs:** 4772
- **Acceptance rate:** 24.77%
- **Average impressions per job:** 1034.87
- **Average job size:** 1.49



Melbourne

- **Total jobs:** 4422
- **Acceptance rate:** 27.23%
- **Average impressions per job:** 1029.56
- **Average job size:** 1.48



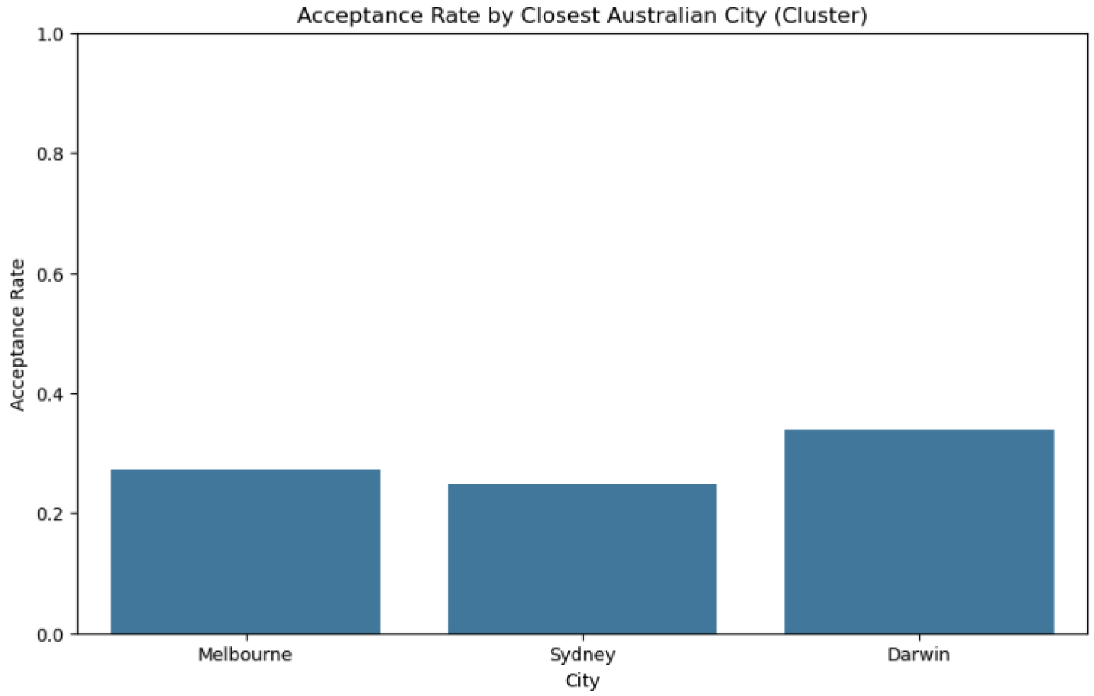
Darwin

- **Total jobs:** 609
- **Acceptance rate:** 33.99%
- **Average impressions per job:** 1020.57
- **Average job size:** 1.52

Note: Stats over time period 2019-09-10 to 2019-09-16
Source: JM Analysis; Python (Jupyter) notebook

Deep dive | Darwin's acceptance rate is higher with statistical significance; an opportune area to test ideas

Acceptance by City Cluster



Acceptance metrics by city cluster

```
   city_cluster  job_count  acceptance_rate
0             0       4422         0.272275
1             1       4772         0.247695
2             2        609         0.339901
ANOVA F-statistic: 13.080205998187632
ANOVA p-value: 2.122791352706383e-06
```

The ANOVA test yielded an F-statistic of **13.08** and a p-value of **2.12e-06**. Very low p-value (<0.05 threshold) indicates that the differences in acceptance rates across these city clusters are statistically significant

Source: JM Analysis; Python (Jupyter) notebook

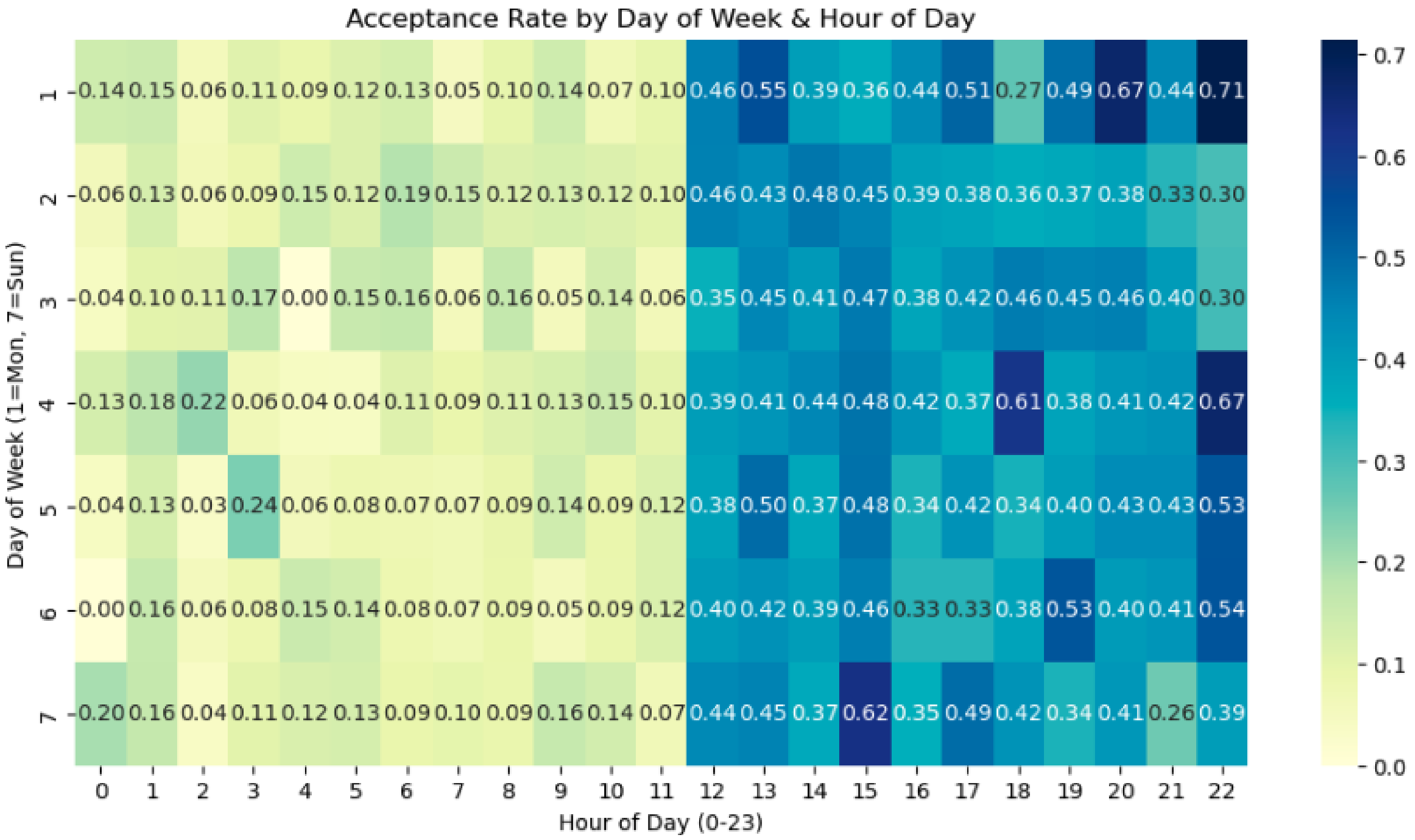
Insight

- Job acceptance rates vary significantly by geographic cluster
- **Darwin** has a noticeably **higher acceptance** rate (34%) **compared to Melbourne and Sydney** (27.2% and 24.8%, respectively)
- Next steps should **investigate specific factors** or strategies in Darwin that contribute to this success—such as tradie availability, local market conditions, or targeted promotions—and consider implementing similar initiatives in across Melbourne and Sydney to boost overall job acceptance rates

Open question | *Do acceptance rates correlate with the distance between job location (latitude/longitude) and the tradie locations?*

We currently only have data for one side of the marketplace, however with another side we would be able to view where tradies are located and where the location of the job is to determine whether distance to job affect acceptance rate

Acceptance rate shifts significantly by time of day, but does not by day of the week



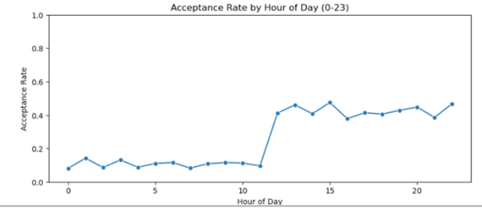
Significantly higher acceptance rates after mid-day regardless of day-of-the-week

Source: JM Analysis; Python (Jupyter) notebook

Deep dive | Acceptance rate optimisations should be focused on time-of-day, as no pattern for day of the week

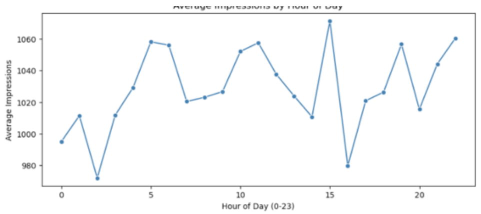
Hour of the day

- **Acceptance rate by hour of the day:** Acceptance rates exhibit a bimodal pattern with peaks around 10 AM and 4-5 PM.



- **Number of jobs posted by hour of the day:** Job postings are most frequent during midday hours, likely when people are home.

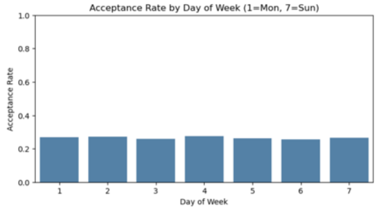
- **Average impressions by hour of the day:** Job impressions generally align with posting activity through the morning and during the day, however at night peak again alongside acceptance rates.



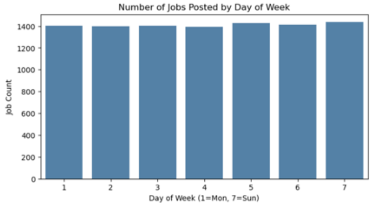
- **Average job size by hour of the day:** Appears to be random variation through the day, indicating lack of pattern.

Day of the week

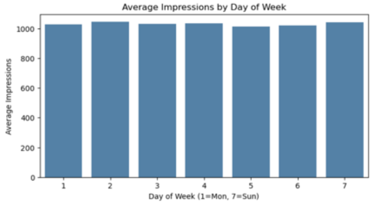
- **Acceptance rate by day of the week**



- **Number of jobs posted by day of the week**



- **Average impressions by day of the week**



- **Average job size by day of the week**

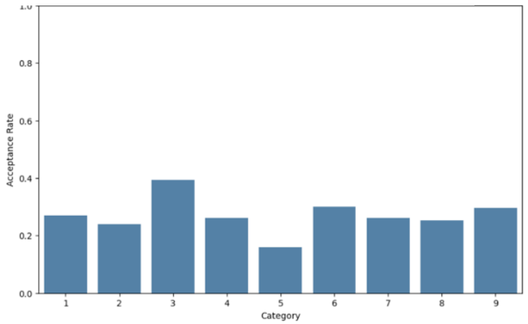
Takeaway!
No pattern by day of the week

Source: JM Analysis; Python (Jupyter) notebook

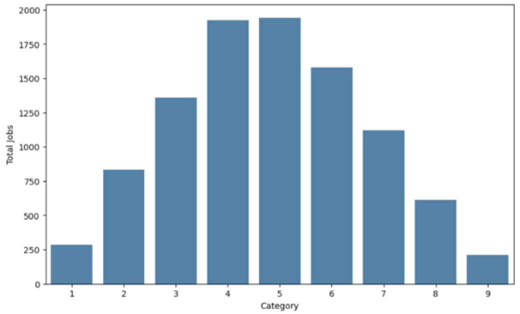
Improvements lie in increasing acceptance rate per category, prioritising high-volume categories

Opportunities for strategic focus

Average acceptance rate by category



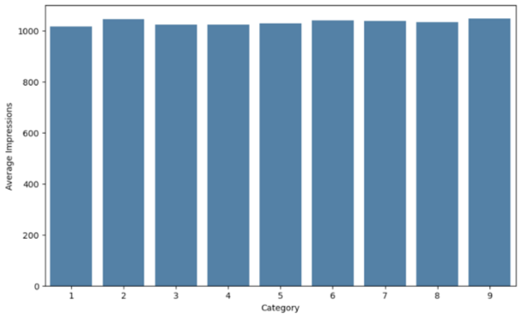
Total jobs by category



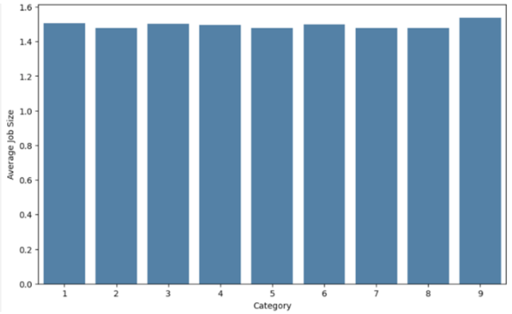
- Some categories **(3 and 6) consistently attract more candidate engagement and acceptance** than others (5). Prioritising high-acceptance categories could optimise job acceptance and completion rates
- Wide variability across acceptance and total jobs posted indicates uneven demand and market saturation. **Focusing on high-volume x high acceptance rate categories for growth could lead to higher overall job conversion rates**

Consistent baseline

Average impressions per job by category



Average job size by category



- **Minimal differences in impressions per job and average job size imply uniform listing behaviour**. Providing lower acceptance jobs per total job (such as category 4 and 5) could improve overall acceptance rate
- Similar job sizes across categories signals standardised demand and role expectations. Streamlining process for categorising jobs could lead to higher acceptance rates by job size

Source: JM Analysis; Python (Jupyter) notebook

Job size is the largest predictor of acceptance rates followed by number of trades

T-test and logistic regression for acceptance criteria

```
T-test for number_of_tradies: p-value=5.097791718548838e-122
Optimization terminated successfully.
         Current function value: 0.523285
         Iterations 6
                           Logit Regression Results
==============================================================================
Dep. Variable:               accepted   No. Observations:                 9870
Model:                          Logit   Df Residuals:                     9866
Method:                           MLE   Df Model:                            3
Date:                Mon, 17 Feb 2025   Pseudo R-squ.:                 0.09427
Time:                        19:37:20   Log-Likelihood:                -5164.8
converged:                       True   LL-Null:                       -5702.4
Covariance Type:            nonrobust   LLR p-value:                 8.908e-233
==========================================================================================
                             coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------
const                     -3.5860      0.109    -32.781      0.000      -3.800      -3.372
number_of_tradies          0.0002   7.96e-06     22.784      0.000       0.000       0.000
estimated_size_numeric     1.1281      0.050     22.615      0.000       1.030       1.226
number_of_impressions  -1.972e-05   5.25e-05     -0.375      0.707      -0.000    8.33e-05
==========================================================================================
```

Simplified output (removed categories and – full output as non-significant). Full model with all variables in following page

Note: Used Logit Regression as a suitable predictor for binary outcomes (job acceptance), because it models the probability of an event occurring based on a set of input variables. By using logit regression, we can identify the most influential factors driving job acceptance and make informed decisions. However, it has limitations in handling non-linear relationships and interactions, making generalized additive models or neural networks potentially more suitable with more input variables.
Source: JM Analysis; Python (Jupyter) notebook

Insight

- **Larger estimated job sizes** increase the likelihood of job acceptance. **A job increase of 1** (e.g. from small to medium) **increases job acceptance by 209%**. This suggests that jobs with higher estimated sizes are more attractive to tradies, which makes intuitive sense
- While **the number of tradies has a statistically significant impact on acceptance**, the effect is relatively minor. In relative terms, all else being equal, **adding +1 tradies** would only lead to a **0.02%** increase in acceptance. This implies that the number of tradies alone is not a decisive factor in job acceptance

!! Corrections
Job size would roughly triple acceptance

$$e^{1.1281} \approx 3.09.$$

Deep dive| Job size is the largest predictor of acceptance rates

T-test and logistic regression for acceptance criteria

```
                           Logit Regression Results
==============================================================================
Dep. Variable:               accepted   No. Observations:                 9870
Model:                          Logit   Df Residuals:                     9855
Method:                           MLE   Df Model:                           14
Date:                Tue, 18 Feb 2025   Pseudo R-squ.:                 0.09500
Time:                        16:19:38   Log-Likelihood:                -5160.7
converged:                       True   LL-Null:                       -5702.4
Covariance Type:            nonrobust   LLR p-value:                1.882e-222
==============================================================================================
                             coef    std err          z      P>|z|      [0.025      0.975]
----------------------------------------------------------------------------------------------
const                     -3.4820      0.205    -16.961      0.000      -3.884      -3.080
number_of_tradies          0.0002   1.12e-05     16.163      0.000       0.000       0.000
estimated_size_numeric     1.1283      0.050     22.609      0.000       1.031       1.226
number_of_impressions  -1.768e-05   5.26e-05     -0.336      0.737      -0.000    8.54e-05
cat_2                     -0.1696      0.165     -1.028      0.304      -0.493       0.154
cat_3                     -0.0424      0.158     -0.269      0.788      -0.351       0.266
cat_4                     -0.0359      0.150     -0.239      0.811      -0.330       0.258
cat_5                     -0.0825      0.158     -0.520      0.603      -0.393       0.228
cat_6                     -0.0887      0.153     -0.581      0.561      -0.388       0.211
cat_7                     -0.0100      0.157     -0.063      0.949      -0.317       0.297
cat_8                     -0.2324      0.172     -1.349      0.177      -0.570       0.105
cat_9                     -0.2929      0.218     -1.342      0.180      -0.721       0.135
city_Melbourne            -0.0187      0.099     -0.189      0.850      -0.213       0.176
city_Sydney               -0.0428      0.101     -0.422      0.673      -0.242       0.156
city_Unknown              -0.1886      0.306     -0.617      0.537      -0.788       0.411
==============================================================================================

T-test for number_of_tradies: p-value=1.8065783014328675e-112
```

Statistical results

- **Pseudo R²** (~0.095) indicates the model explains ~9.5% of variance (low but common for binary outcomes) of the acceptance variation— leaves room for additional factors (e.g., job urgency, tradie specialisation)
- **Where P > Z is > 0.05** not enough evidence to state that number of impressions is statistically significant
- **Estimated_size_numeric** (coef=1.128, p=0.000) and **number_of_trades** (coef=0.0002, p≈0) are the only significant predictors
- **Removed category 1 (cat_1)** to remove p=1.0 collinearity effects for all categories and cities

Model weaknesses & possible follow up steps

- Model uses non-robust standard errors; consider re-running with robust errors to check for heteroscedasticity
- Investigate reference categories for cat_1 and baseline city (likely omitted and driving non-significance in others)

Note: Used Logit Regression as a suitable predictor for binary outcomes (job acceptance), because it models the probability of an event occurring based on a set of input variables. By using logit regression, we can identify the most influential factors driving job acceptance and make informed decisions. However, it has limitations in handling non-linear relationships and interactions, making generalized additive models or neural networks potentially more suitable with more input variables.
Source: JM Analysis; Python (Jupyter) notebook

Insight has led to several direct recommendations

Recommendations

	Regional Focus	Time & Scheduling	Job Category Performance	Model Insights & Key Predictors
Insight	Darwin experiences significantly higher acceptance rates	Build initial user adoption in a small, targeted area	Certain categories have higher acceptance vs. other categories	Job Size is the largest driver of acceptance
Actions	• **Replicate Darwin's Success:** Investigate why Darwin achieves a higher acceptance rate despite lower volume and consider piloting similar strategies in Sydney and Melbourne	• **Test Off-Peak Promotions:** Explore targeted promotions during off-peak hours to potentially smooth out acceptance fluctuations	• **Reassess Underperforming Categories:** For categories with lower acceptance rates, investigate causes and consider consolidating or reclassifying similar categories to optimise performance	• **Large Jobs:** Since size is a strong predictor, promote or highlight higher-value jobs to tradies, possibly bundling smaller tasks or offering specialized coverage for complex work
Expected Outcome	• **5–10 percentage point improvement in** acceptance across Melbourne and Sydney	• **Smoother job fulfillment** across time of day	• **Faster job matching** and a higher volume of successfully completed jobs	• **Higher overall job basket size completed**, leading to higher revenue for trades

Execute recommendations across insight categories to validate the recommendation platform, build traction, and scale sustainably

Appendix

Steps to clean data

Steps to clean data

1. Load & Inspect
- Create a new instance and load the CSV into BigQuery
- Check row counts, column names, and data types

2. Clean Missing / Invalid Values
- Identify nulls in latitude, longitude, category, number_of_tradies, estimated_size, number_of_impressions, accepted
- Decide whether to impute, drop, or otherwise handle missing values

3. Handle Outliers
- Identify outliers in estimated_size, number_of_tradies, or number_of_impressions
- Decide whether to cap, remove, or transform the outliers

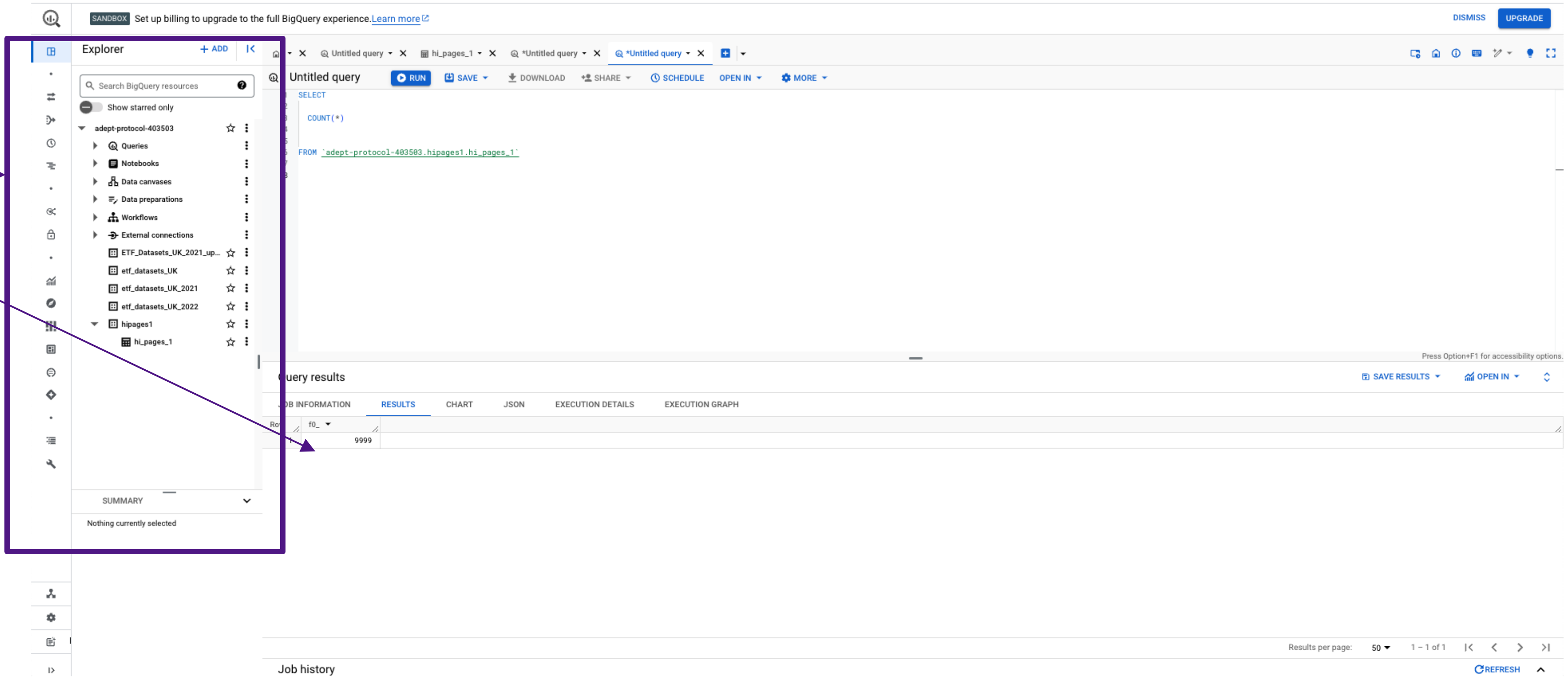
3. Enhance Data
- Add extract features to data to check acceptance patterns later
- Fields to add include: hour of day, day of week, month, and weekend vs. weekday (boolean)

4. Extract Cleaned Data for Further Manipulation
- Extract cleaned data as .csv to be used for further manipulation by Tableau, Python, etc.

1. Load and inspect data

Insight

- Load all data into BigQuery to process
- Discovered 9999 rows



2. **Clean Missing / Invalid Values**

Untitled query   RUN   SAVE   DOWNLOAD   SHARE   SCHEDULE   OPEN IN   MORE

```
SELECT
  COUNT(*) AS total_rows,
  COUNTIF(latitude IS NULL) AS null_latitude,
  COUNTIF(` longitude` IS NULL) AS null_longitude,
  COUNTIF(category IS NULL) AS null_category,
  COUNTIF(number_of_tradies IS NULL) AS null_number_of_tradies,
  COUNTIF(estimated_size IS NULL) AS null_estimated_size,
  COUNTIF(number_of_impressions IS NULL) AS null_number_of_impressions,
  COUNTIF(accepted IS NULL) AS null_accepted


FROM `adept-protocol-403503.hipages1.hi_pages_1`
```

Query results

JOB INFORMATION   RESULTS   CHART   JSON   EXECUTION DETAILS   EXECUTION GRAPH

Row	total_rows	null_latitude	null_longitude	null_category	null_number_of_trad	null_estimated_size	null_number_of_impı	null_accepted
1	9999	0	0	0	0	0	110	0

Insight

- Longitude requires ' ' space in string when writing query, otherwise receive errors
- Discovered 110 null impressions

2. **Clean Missing / Invalid Values**

Untitled query

RUN SAVE DOWNLOAD SHARE SCHEDULE OPEN IN MORE

```sql
WITH stats AS (
  SELECT
    COUNT(*) AS total_rows,
    COUNTIF(number_of_impressions IS NULL) AS missing_impressions,
    -- Calculate the median (50th percentile) for number_of_impressions
    APPROX_QUANTILES(number_of_impressions, 101)[OFFSET(50)] AS median_impressions
  FROM `adept-protocol-403503.hipages1.hi_pages_1`
)
SELECT
  total_rows,
  missing_impressions,
  (missing_impressions / total_rows) * 100 AS missing_percentage,
  median_impressions
FROM stats;
```

Query results

JOB INFORMATION | RESULTS | CHART | JSON | EXECUTION DETAILS | EXECUTION GRAPH

Row	total_rows	missing_impressions	missing_percentage	median_impressions
1	9999	110	1.1001100110011002	1001

Insight

- Percentage missing impressions ~1.1%
- As percentage <5%, moving on to assess the distribution

2. **Clean Missing / Invalid Values**

Untitled query | RUN | SAVE | DOWNLOAD | SHARE | SCHEDULE | OPEN IN | MORE

```sql
SELECT
  EXTRACT(DATE FROM time_of_post) AS post_date,
  COUNT(*) AS total_rows,
  COUNTIF(number_of_impressions IS NULL) AS missing_impressions_count,
  (COUNTIF(number_of_impressions IS NULL) / COUNT(*)) * 100 AS missing_percentage
FROM `adept-protocol-403503.hipages1.hi_pages_1`
GROUP BY post_date
ORDER BY post_date;
```

Query results

JOB INFORMATION | RESULTS | CHART | JSON | EXECUTION DETAILS | EXECUTION GRAPH

Row	post_date	total_rows	missing_impressions_coun	missing_percentage
1	2019-09-10	1417	14	0.98800282286…
2	2019-09-11	1418	14	0.98730606488…
3	2019-09-12	1419	17	1.19802677942…
4	2019-09-13	1451	14	0.96485182632…
5	2019-09-14	1423	16	1.12438510189…
6	2019-09-15	1455	17	1.16838487972…
7	2019-09-16	1416	18	1.27118644067…

Insight

- Each day, ~1% of the rows have missing values
- % of missing values is consistent from day to day. There isn't any day with a significantly higher percentage of missing values, suggesting data is evenly distributed across the dates
- Given their low frequency (<5%) and even distribution, best to impute data by replacing missing values with the median

2. **Clean Missing / Invalid Values**

Untitled query RUN SAVE DOWNLOAD SHARE SCHEDULE OPEN IN MORE

```sql
WITH stats AS (
  SELECT
    APPROX_QUANTILES(number_of_impressions, 101)[OFFSET(50)] AS median_impressions
  FROM `adept-protocol-403503.hipages1.hi_pages_1`
)
SELECT
  time_of_post,
  latitude,
  -- Cleaned column: removed the leading space by aliasing
  ` longitude` AS longitude,
  category,
  number_of_tradies,
  estimated_size,
  COALESCE(number_of_impressions, s.median_impressions) AS number_of_impressions,
  accepted
FROM `adept-protocol-403503.hipages1.hi_pages_1` t
CROSS JOIN stats s;
```

Query results

JOB INFORMATION | RESULTS | CHART | JSON | EXECUTION DETAILS | EXECUTION GRAPH

Row	time_of_post	latitude	longitude	category	number_of_tradies	estimated_size	number_of_impressi	accepted
1	2019-09-15 08:59:06 UTC	-33.8712	151.2583	5	355	medium	1531	0
2	2019-09-15 17:36:06 UTC	-34.053	151.494	5	355	medium	1139	0
3	2019-09-14 04:40:06 UTC	-33.9201	151.1116	5	355	medium	1357	0
4	2019-09-16 11:37:06 UTC	-33.9341	151.1824	5	355	medium	647	0
5	2019-09-14 05:22:06 UTC	-33.8119	151.2172	5	355	medium	834	0
6	2019-09-12 08:50:06 UTC	-33.9156	151.2732	5	355	medium	1020	0
7	2019-09-16 07:02:06 UTC	-33.8594	151.3541	5	355	medium	1113	1
8	2019-09-16 17:46:06 UTC	-33.8221	151.3462	5	355	medium	1505	1
9	2019-09-13 21:24:06 UTC	-33.7683	151.0795	5	355	medium	1654	1
10	2019-09-13 12:22:06 UTC	-33.9906	151.2514	5	355	medium	18	0
11	2019-09-15 02:09:06 UTC	-33.8226	151.3104	5	355	medium	1976	0
12	2019-09-14 12:42:06 UTC	-33.8761	151.2526	5	355	medium	1529	1
13	2019-09-10 09:54:06 UTC	-33.9338	151.3495	5	355	medium	1260	1

Insight

- Changed ‘ longitude’ column to longitude to make it easier to read
- Replaced % missing values for number_of_impressions with 50th percentile (median) figures using Caolesce

3. **Handle Outliers**

Logic to handle outliers

Step 1: Assess the Frequency of Outliers
If the percentage of outliers is:
- Less than 1%: Proceed to Step 2
- Between 1% and 5%: Consider capping (Step 3) or removal (Step 4)
- Greater than 5%: Consider removal (Step 4) or transformation (Step 5)

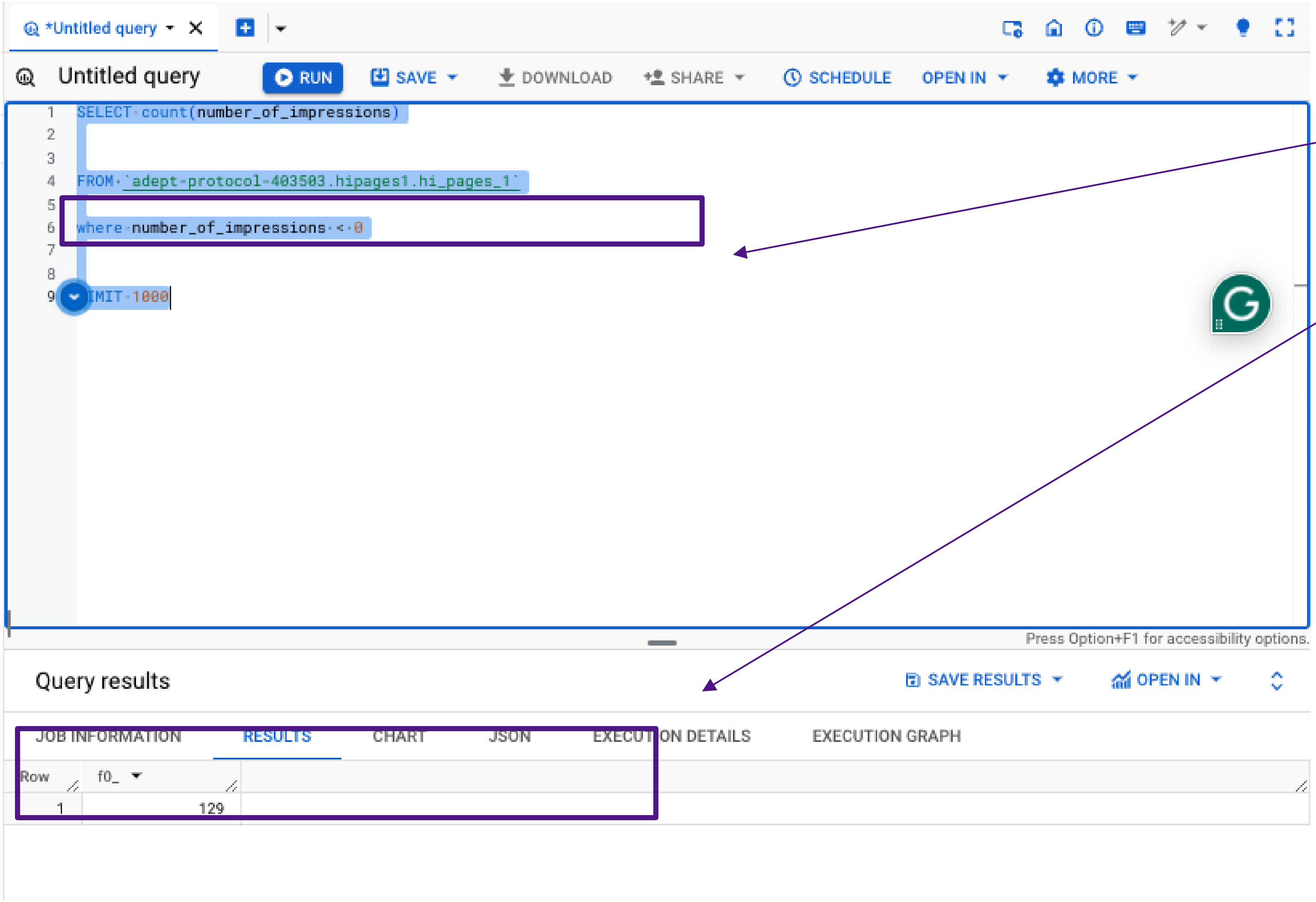
Step 2: Assess the Distribution of Outliers
Check if the outliers are:
- Randomly scattered: Proceed to Step 3
- Concentrated in specific rows or columns: Consider removal (Step 4)

Step 3: Capping
If the outliers are in a:
- Numerical column: Cap at the 95th percentile or 3 standard deviations from the mean
- Categorical column: Not applicable
- Datetime column: Not applicable

Step 4: Removal
If the outliers are:
- Concentrated in specific rows: Delete these rows
- Concentrated in specific columns: Consider deleting those columns
- Causing significant skewness or bias: Remove them

Step 5: Transformation
If the outliers are:
- Causing significant skewness or bias: Apply transformations (e.g., log, square root)

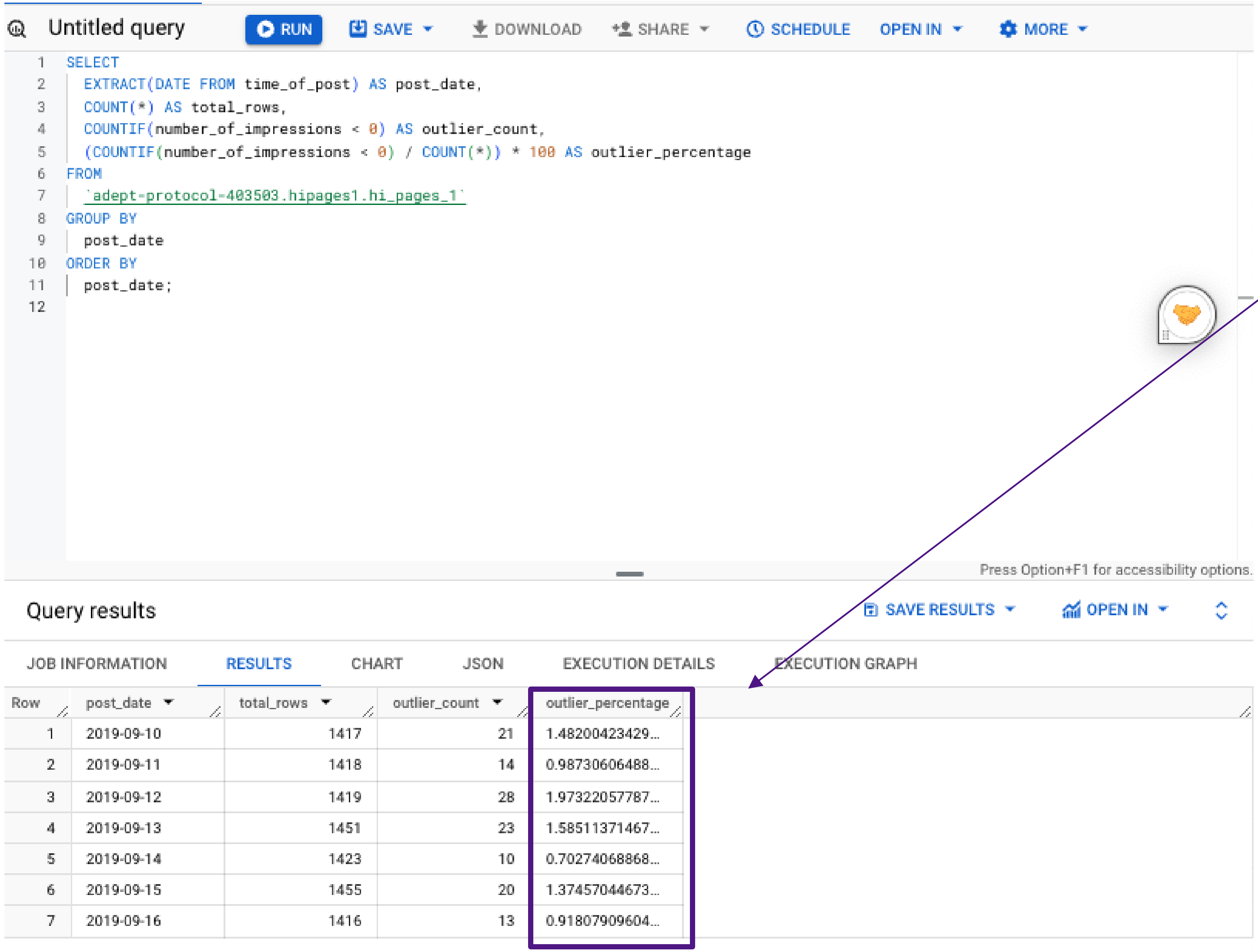
3. **Handle Outliers**



Insight

- Found that 129 (~1%) of columns are negative for number_of_impressions
- Negative impressions do not make logical sense

3. Handle Outliers

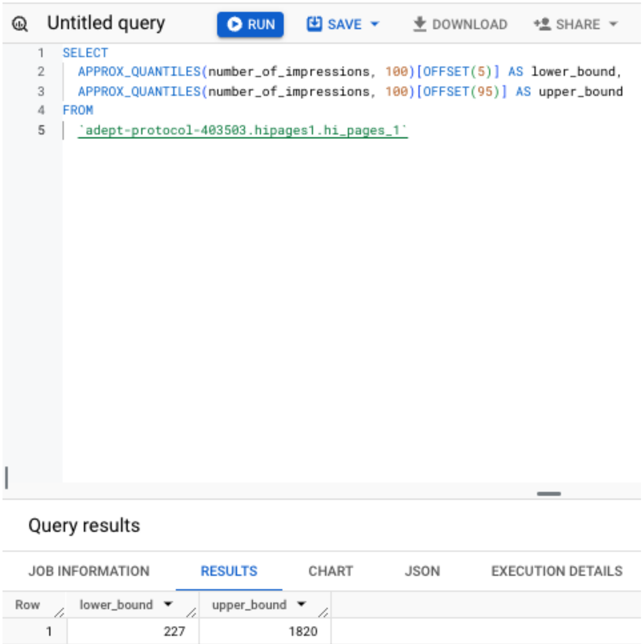



```sql
SELECT
  EXTRACT(DATE FROM time_of_post) AS post_date,
  COUNT(*) AS total_rows,
  COUNTIF(number_of_impressions < 0) AS outlier_count,
  (COUNTIF(number_of_impressions < 0) / COUNT(*)) * 100 AS outlier_percentage
FROM
  `adept-protocol-403503.hipages1.hi_pages_1`
GROUP BY
  post_date
ORDER BY
  post_date;
```

Row	post_date	total_rows	outlier_count	outlier_percentage
1	2019-09-10	1417	21	1.48200423429...
2	2019-09-11	1418	14	0.98730606488...
3	2019-09-12	1419	28	1.97322057787...
4	2019-09-13	1451	23	1.58511371467...
5	2019-09-14	1423	10	0.70274068868...
6	2019-09-15	1455	20	1.37457044673...
7	2019-09-16	1416	13	0.91807909604...

Insight

- Found that 129 randomly sprea
- Cap the outliers a 0 base, which is a positive figure




```sql
SELECT
  APPROX_QUANTILES(number_of_impressions, 100)[OFFSET(5)] AS lower_bound,
  APPROX_QUANTILES(number_of_impressions, 100)[OFFSET(95)] AS upper_bound
FROM
  `adept-protocol-403503.hipages1.hi_pages_1`
```

Row	lower_bound	upper_bound
1	227	1820

4. **Enhance data**

Untitled query

RUN SAVE DOWNLOAD SHARE SCHEDULE OPEN IN MORE

```sql
WITH stats AS (
  SELECT
    APPROX_QUANTILES(number_of_impressions, 101)[OFFSET(50)] AS median_impressions
  FROM `adept-protocol-403503.hipages1.hi_pages_1`
)
SELECT
  -- Original columns
  time_of_post,
  latitude,
  ` longitude` AS longitude,  -- Alias to remove the leading space
  category,
  number_of_tradies,
  estimated_size,
  COALESCE(number_of_impressions, s.median_impressions) AS number_of_impressions,
  accepted,

  -- New time-based features
  EXTRACT(HOUR FROM time_of_post) AS hour_of_day,
  MOD(EXTRACT(DAYOFWEEK FROM time_of_post) + 5, 7) + 1 AS day_of_week,
  EXTRACT(MONTH FROM time_of_post) AS month,
  CASE
    WHEN MOD(EXTRACT(DAYOFWEEK FROM time_of_post) + 5, 7) + 1 IN (6, 7) THEN TRUE
    ELSE FALSE
  END AS is_weekend

FROM `adept-protocol-403503.hipages1.hi_pages_1` t
CROSS JOIN stats s

ORDER BY 1;
```

Query results

JOB INFORMATION | RESULTS | CHART | JSON | EXECUTION DETAILS | EXECUTION GRAPH

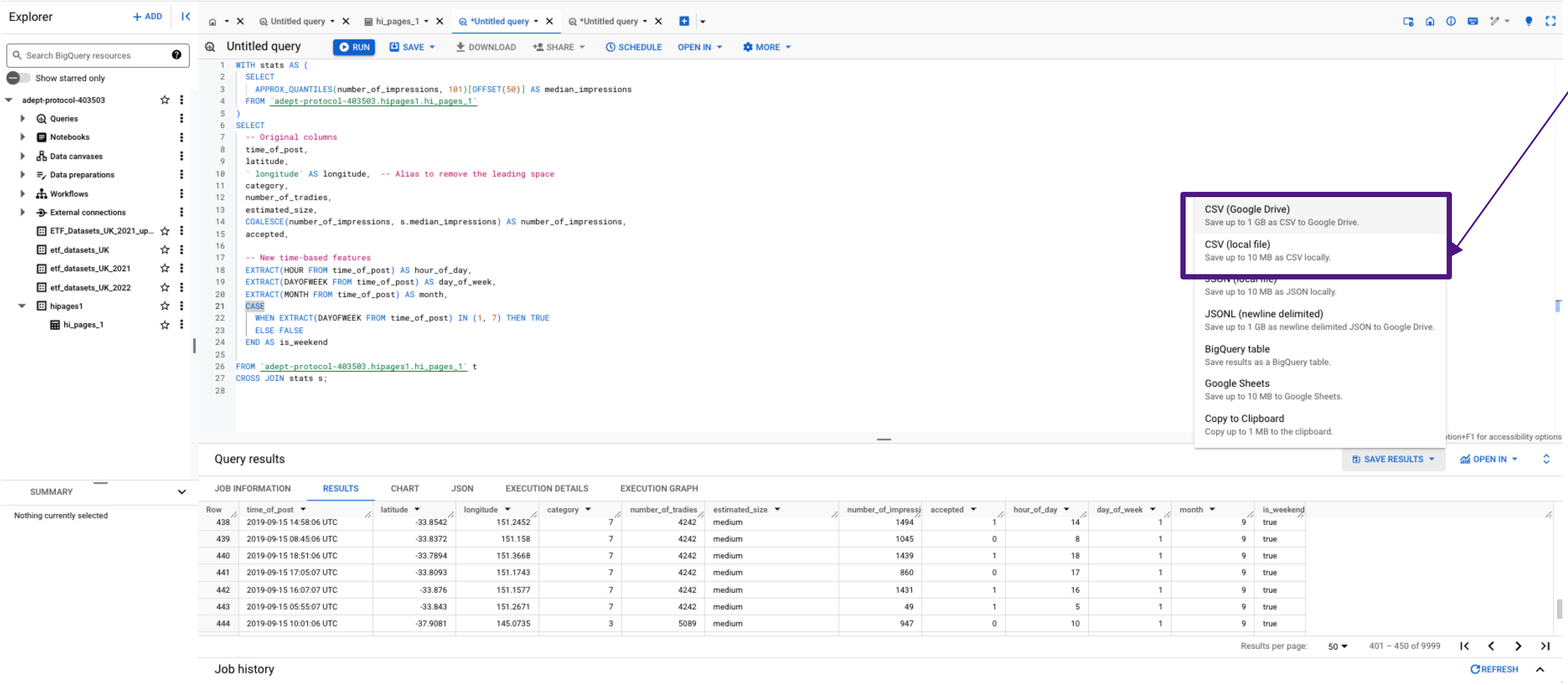
Row	time_of_post	latitude	longitude	category	number_of_tradies	estimated_size	number_of_impressi	accepted	hour_of_day	day_of_week	month	is_weekend
1	2019-09-10 00:01:06 UTC	-37.8864	145.0756	8	8376	medium	275	0	0	2	9	false
2	2019-09-10 00:05:06 UTC	-33.8586	151.3561	9	10000	medium	1323	0	0	2	9	false
3	2019-09-10 00:15:06 UTC	-33.8141	151.0705	2	7331	small	859	0	0	2	9	false
4	2019-09-10 00:16:06 UTC	-17.9496	122.0574	3	10000	small	832	0	0	2	9	false
5	2019-09-10 00:21:06 UTC	-34.0679	151.1331	6	2476	small	907	0	0	2	9	false
6	2019-09-10 00:22:06 UTC	-17.8035	122.359	5	3590	small	1311	0	0	2	9	false
7	2019-09-10 00:23:06 UTC	-33.9631	151.2392	3	9732	medium	825	1	0	2	9	false

Insight

Added other columns to make the data easier to manipulate later:

- hour_of_day
- day_of_week
- month
- is_weekend (boolean)

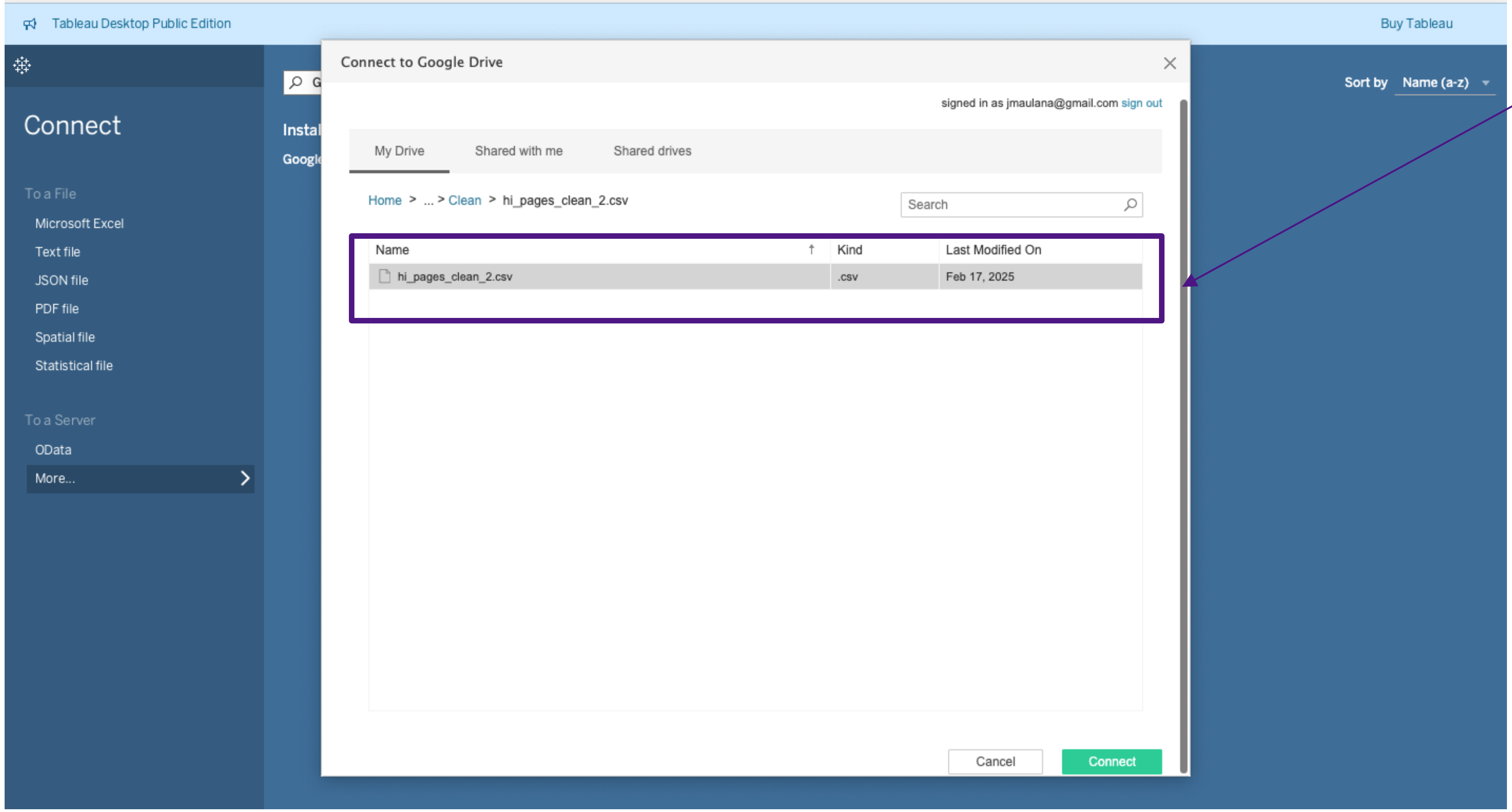
5. **Extract Cleaned Data for Further Manipulation**



Insight

Downloaded as .csv and downloaded and loaded into GitHub

5. **Extract Cleaned Data for Further Manipulation**



Insight

Connect to Tableau

Deep dive| Our model is a strong predictor of outcomes

T-test and logistic regression for acceptance criteria

Logit Regression Results

Dep. Variable:	accepted	No. Observations:	9870
Model:	Logit	Df Residuals:	9855
Method:	MLE	Df Model:	14
Date:	Tue, 18 Feb 2025	Pseudo R-squ.:	0.09500
Time:	16:19:38	Log-Likelihood:	-5160.7
converged:	True	LL-Null:	-5702.4
Covariance Type:	nonrobust	LLR p-value:	1.882e-222

	coef	std err	z	P>|z|	[0.025	0.975]
const	-3.4820	0.205	-16.961	0.000	-3.884	-3.080
number_of_tradies	0.0002	1.12e-05	16.163	0.000	0.000	0.000
estimated_size_numeric	1.1283	0.050	22.609	0.000	1.031	1.226
number_of_impressions	-1.768e-05	5.26e-05	-0.336	0.737	-0.000	8.54e-05
cat_2	-0.1696	0.165	-1.028	0.304	-0.493	0.154
cat_3	-0.0424	0.158	-0.269	0.788	-0.351	0.266
cat_4	-0.0359	0.150	-0.239	0.811	-0.330	0.258
cat_5	-0.0825	0.158	-0.520	0.603	-0.393	0.228
cat_6	-0.0887	0.153	-0.581	0.561	-0.388	0.211
cat_7	-0.0100	0.157	-0.063	0.949	-0.317	0.297
cat_8	-0.2324	0.172	-1.349	0.177	-0.570	0.105
cat_9	-0.2929	0.218	-1.342	0.180	-0.721	0.135
city_Melbourne	-0.0187	0.099	-0.189	0.850	-0.213	0.176
city_Sydney	-0.0428	0.101	-0.422	0.673	-0.242	0.156
city_Unknown	-0.1886	0.306	-0.617	0.537	-0.788	0.411

T-test for number_of_tradies: p-value=1.8065783014328675e-112

Statistical results

- DF Model 14: things being tested
- LL-NULL < Log Likelihood: Model is decent predictor
- LLR p-value < 0.05 (and small): Model is decent predictor of fit

- P-value <0.05 (and extremely small) indicates that there is extremely low levels that our model does NOT explain the real effect of changes observed

Note: Used Logit Regression as a suitable predictor for binary outcomes (job acceptance), because it models the probability of an event occurring based on a set of input variables. By using logit regression, we can identify the most influential factors driving job acceptance and make informed decisions. However, it has limitations in handling non-linear relationships and interactions, making generalized additive models or neural networks potentially more suitable with more input variables.
Source: JM Analysis; Python (Jupyter) notebook