Deel

Growth Analytics Challenge

Task 1

Analysing Sales Data Funnel

a) Time series analysis

- Perform a time series analysis on the number of:
  - demo occurrences
  - sales qualified opportunities
  - closed won opportunities.

- Are there any seasonality patterns in the data?
  - If so: how can we use this information for marketing strategy planning?

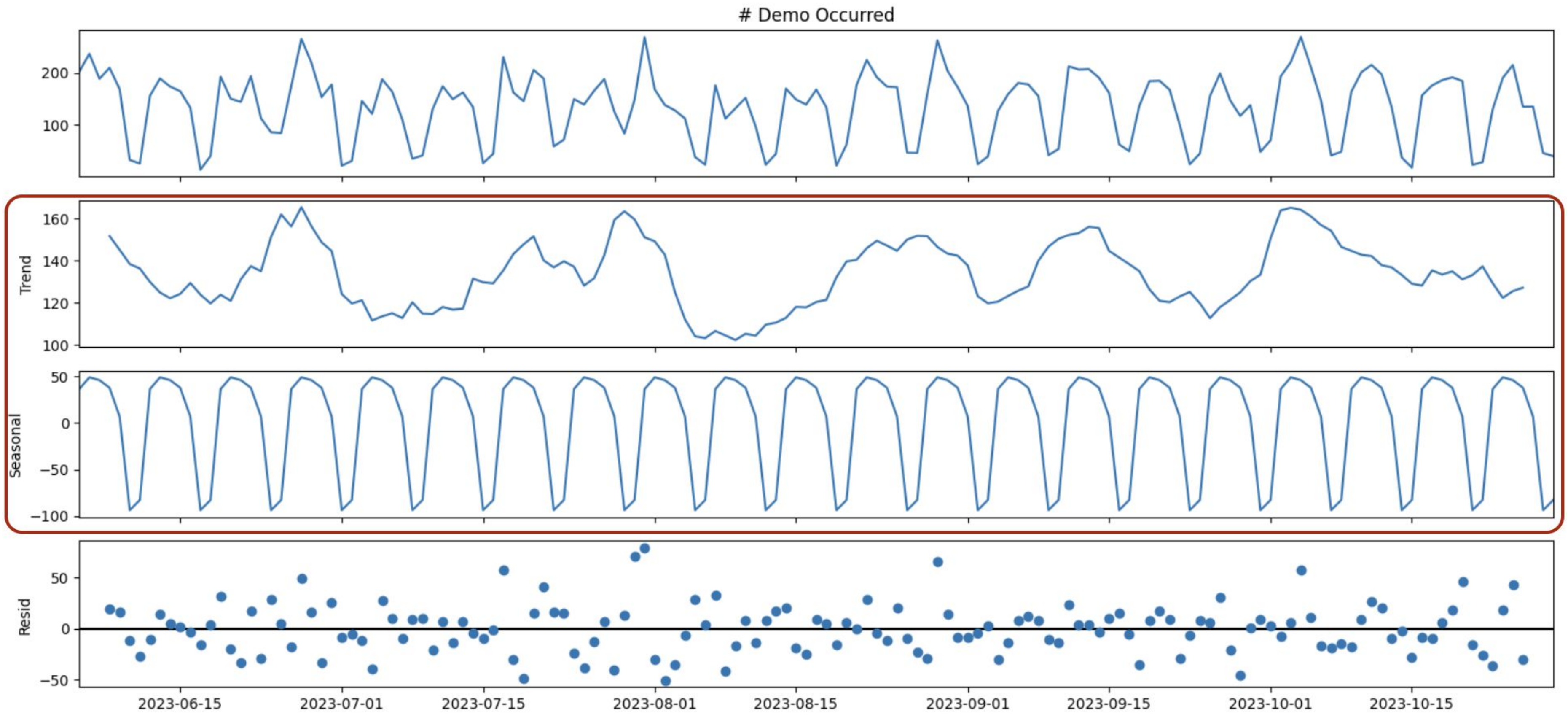

Demo Occurred
200
100
2023-06
2023-07
2023-08
2023-09
2023-10
2023-11
Original: # Demo Occurred
Rolling: # Demo Occurred
Sales Qualified Opportunity
150
100
50
0
2023-06
2023-07
2023-08
2023-09
2023-10
2023-11
Original: # Sales Qualified Opportunity
Rolling: # Sales Qualified Opportunity
Closed Won Opportunity
75
50
25
0
2023-06
2023-07
2023-08
2023-09
2023-10
2023-11
Original: # Closed Won Opportunity
Rolling: # Closed Won Opportunity

Evaluation

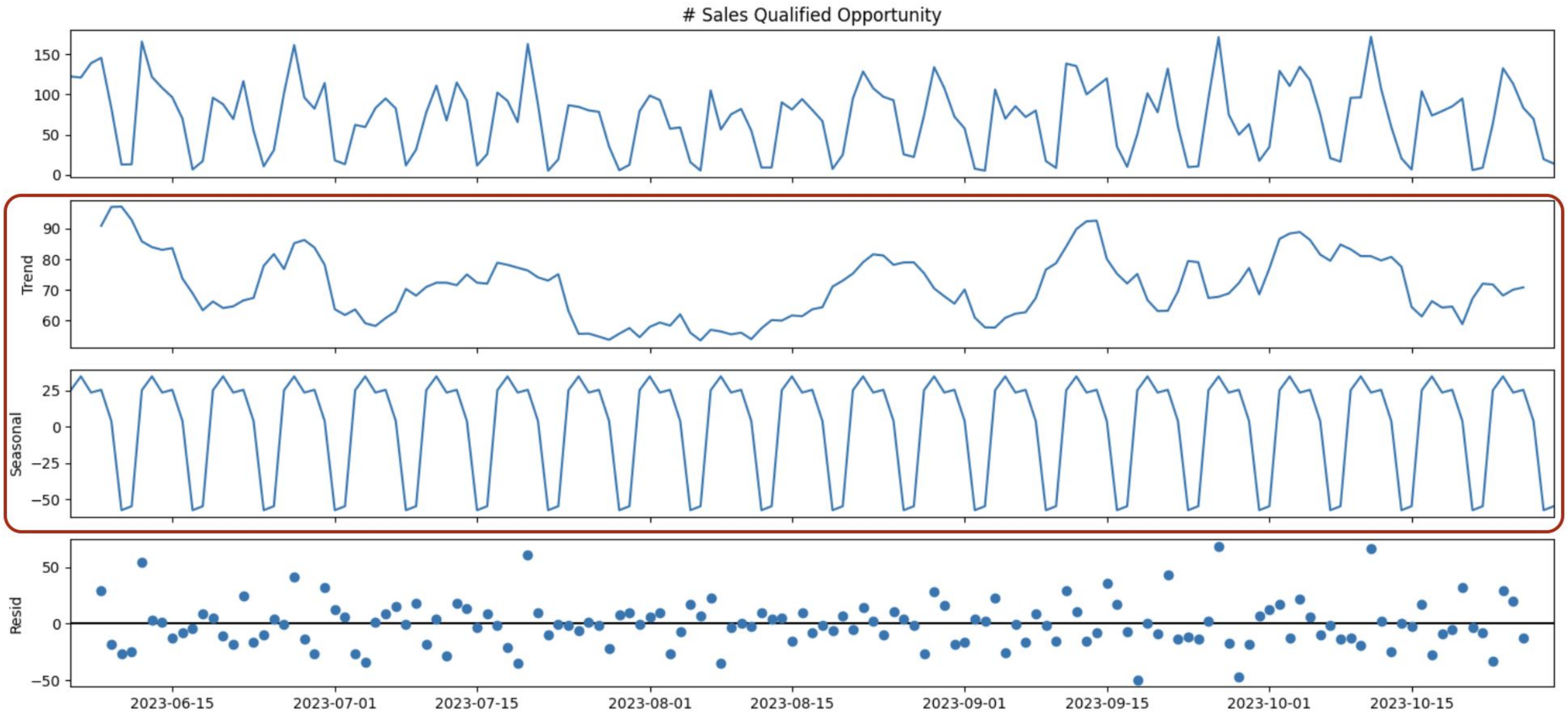
- The funnel data shows ***significant patterns of seasonality***
- The data suggests there are ***no Demos / Sales / Closed opportunities on weekends***
- This is highly plausible, given the 5-day work week (Mon-Fri)

Next Steps

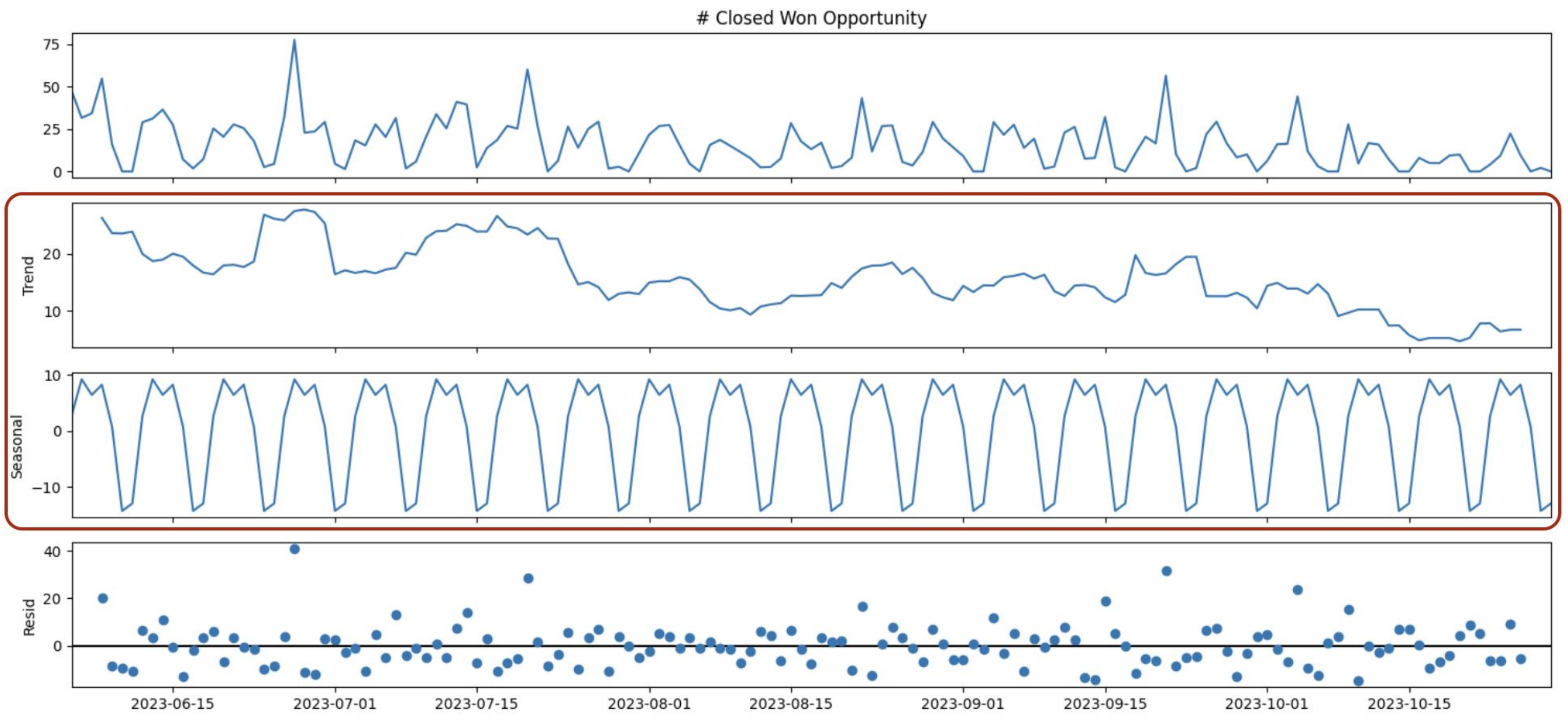
- We run a ***time series decomposition***, with a 7-day period, due to our assumption of the weekly cyclical nature of the daily data
- This decomposition shows:
  - seasonality in the data
  - trend of the data
  - Residuals (variation which can't be attributed to the seasonality / trend



Demo Occurred
Trend
Seasonal
Resid
2023-06-15
2023-07-01
2023-07-15
2023-08-01
2023-08-15
2023-09-01
2023-09-15
2023-10-01
2023-10-15



Sales Qualified Opportunity
Trend
Seasonal
Resid
2023-06-15
2023-07-01
2023-07-15
2023-08-01
2023-08-15
2023-09-01
2023-09-15
2023-10-01
2023-10-15



Closed Won Opportunity
Trend
Seasonal
Resid
2023-06-15
2023-07-01
2023-07-15
2023-08-01
2023-08-15
2023-09-01
2023-09-15
2023-10-01
2023-10-15

Analysis

- High daily seasonality in all 3 funnel KPIs
- Demos / Sales Qualified opportunities:
    - Generally stable over the timeframe
    - Consistently lower values at the start of the month
    - Increasing from the middle towards the end of the month, before declining again
- Closed Opportunities:
    - Trending downwards, with a major decrease towards the end of July

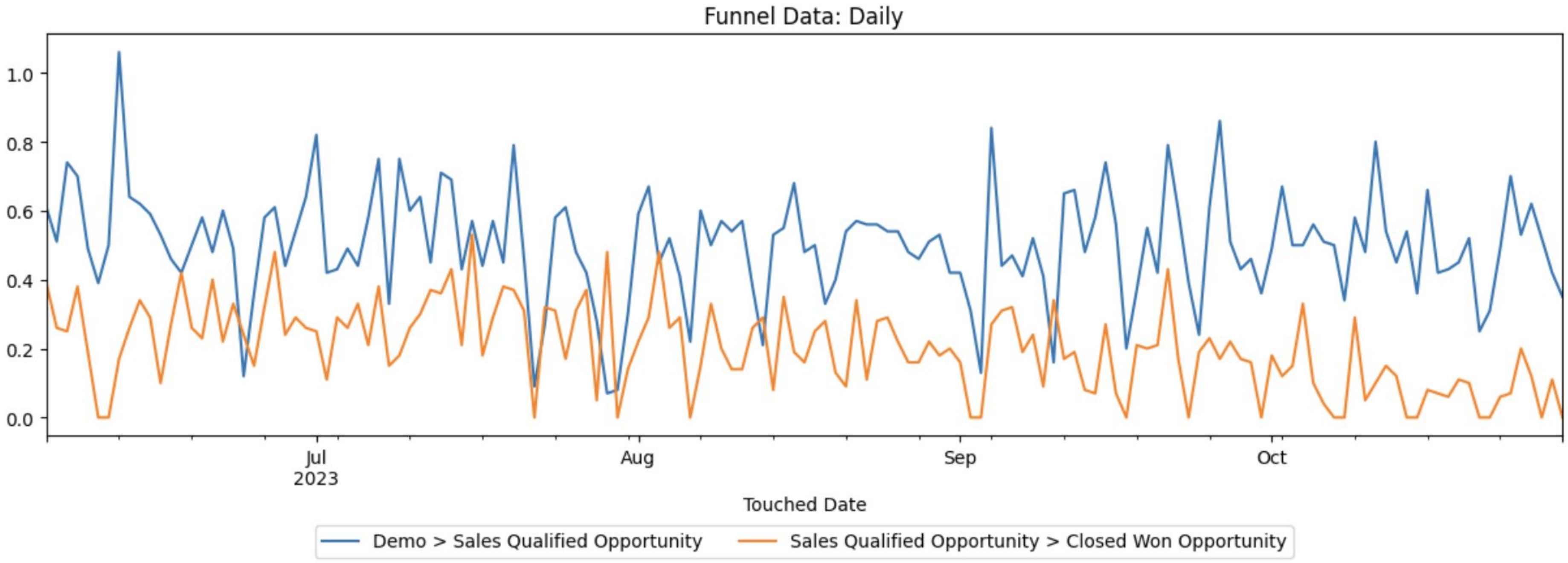
Recommendations

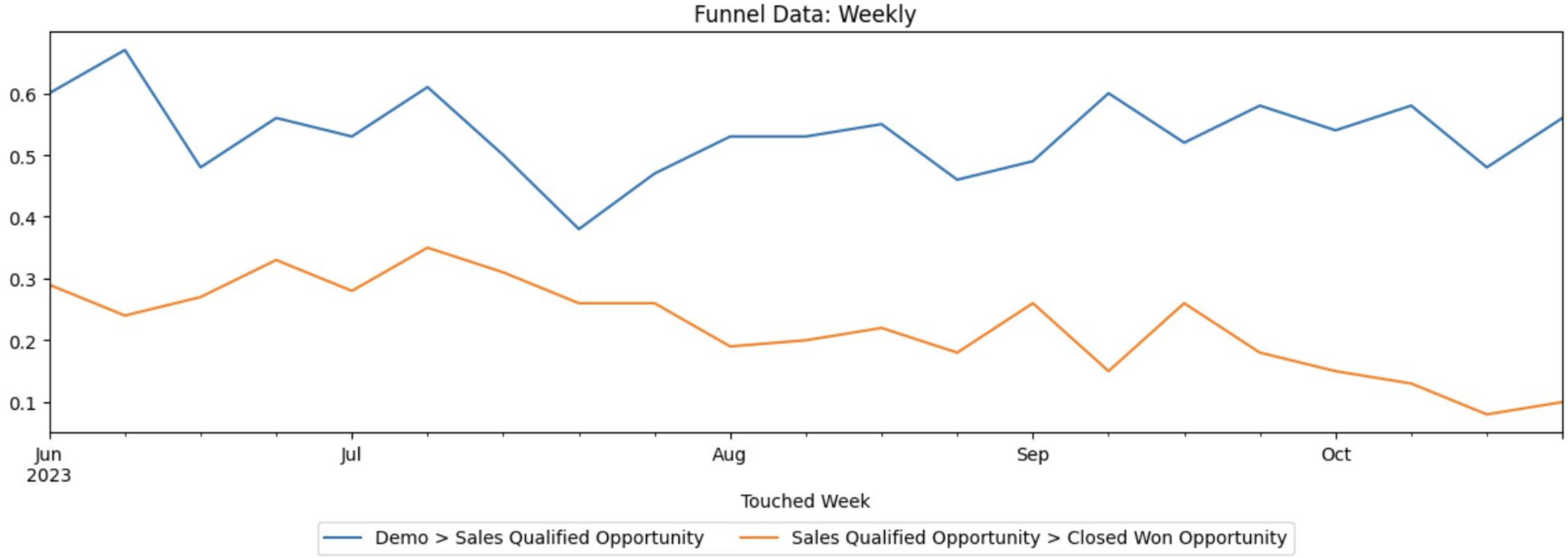
- Marketing budgets should be ***disproportionately allocated to the working week*** (Mon-Fri)
- ***Lower proportion of budget allocated to the start of the month***
- Given the stable demos / sales opportunities but lower closed opportunities:
    - We could develop many hypotheses why this is occurring, but we might ***consider a general reduction in budget***

b) Funnel conversion rate

- Calculate the conversion rates for the sales funnel over time, from:
    - *Demo Occurred* to *Sales Qualified Opportunity*
    - *Sales Qualified Opportunity* to *Closed Won Opportunity*

- Provide visualizations to illustrate these trends.


Funnel Data: Daily
1.0
0.8
0.6
0.4
0.2
0.0
Jul
2023
Aug
Sep
Oct
Touched Date
Demo > Sales Qualified Opportunity
Sales Qualified Opportunity > Closed Won Opportunity


Funnel Data: Weekly
0.6
0.5
0.4
0.3
0.2
0.1
Jun
2023
Jul
Aug
Sep
Oct
Touched Week
Demo > Sales Qualified Opportunity
Sales Qualified Opportunity > Closed Won Opportunity

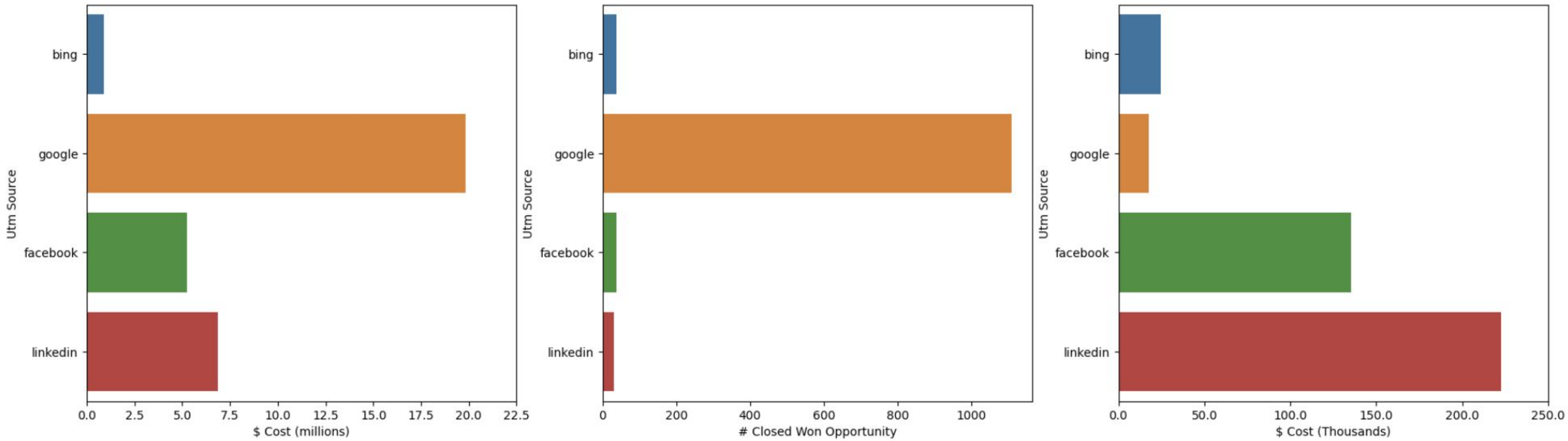
Analysis

- Daily data shows high variance, possible due to data seasonality
- Time series decomposition outside the scope of this question
- Weekly data shows:
  - Generally ***stable 'Demo > Sales Qualified Opportunity'***
  - ***Decrease 'Sales Qualified Opportunity > Closed Won Opportunity'***

c) CPA | Medium & Source combinations

- Calculate the Cost Per Acquisition (CPA) for:
    - UTM medium and source combinations that cost data is provided.

- How does the CPA vary across different marketing channels?



	Utm Medium	Utm Source	$ Cost	# Closed Won Opportunity	cpa
1	paid-search	google	19820244.0	1110.8	17843.0
0	paid-search	bing	906303.0	36.6	24762.0
2	paid-social	facebook	5243682.0	38.8	135146.0
3	paid-social	linkedin	6876231.0	30.9	222532.0

Analysis

- CPA's vary significantly:
    - Paid-search (€18,000-€25,000) significantly more efficient than paid-social (€135,000-€222,000)

- Google is by far the best performing paid channel, in terms of:
    - Scale ($ Cost) & Efficiency (CPA), driving the overwhelming majority of #closed won opportunities

- Bing, whilst less efficient and much less scaled than Google, is much more efficient CPA's than paid-social channels

- Facebook and Linkedin, based on this dataset, show decent scale at very low efficiency

d) Funnel conversion rate insights

- Provide insights and recommendations on how to optimize the marketing strategy based on the sales funnel data
- Which channels or campaigns should be prioritized for future marketing efforts

Proposal

Bid Adjustments based on over / underperforming campaigns

Assumptions

- There is a scale <> efficiency trade off in marketing
- Easiest way to control this is by increasing / decrease campaign bids

Strategy

- Spend more on efficient campaigns & spend less on inefficient campaigns
- Ideally we would use the campaign ROAS
- We will use *'Demo > Closed Won Opportunity rate'* as a proxy

Approach

- Limit dataset to: paid-search & paid-social
- Calculate Average: *'Demo > Closed Won Opportunity rate'* across the entire dataset ***(8.3%)***
- For each campaign: Compare *'Demo > Closed Won Opportunity rate'* with the Average, if:
  - Campaign value > average value: **Increase Bid**
  - Campaign value < average value: **Decrease Bid**

Approach

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Efficient Campaigns Sample

	Utm Source	Utm Campaign	# Demo Occurred	# Sales Qualified Opportunity	# Closed Won Opportunity	Demo > Sales Qualified Opportunity	Sales Qualified Opportunity > Closed Won Opportunity	Demo > Closed Won Opportunity	Bidding Decision
558	google	nam-t1_acq_searchbrand_google_search_broad--__all	1854.6	1427.7	299.0	0.77	0.21	0.16	Increase Bid
441	google	emea-t1a_acq_searchbrand_google_search_broad--...	930.8	657.6	151.5	0.71	0.23	0.16	Increase Bid
573	google	nam-t1_acq_searchnonbranded_google_search_coun...	399.1	238.7	36.0	0.60	0.15	0.09	Increase Bid

Inefficient Campaigns Sample

	Utm Source	Utm Campaign	# Demo Occurred	# Sales Qualified Opportunity	# Closed Won Opportunity	Demo > Sales Qualified Opportunity	Sales Qualified Opportunity > Closed Won Opportunity	Demo > Closed Won Opportunity	Bidding Decision
459	google	emea-t1a_acq_searchnonbranded_google_search_pa...	352.9	168.6	18.2	0.48	0.11	0.05	Decrease Bid
578	google	nam-t1_acq_searchnonbranded_google_search_payr...	501.4	136.1	15.8	0.27	0.12	0.03	Decrease Bid
574	google	nam-t1_acq_searchnonbranded_google_search_eor-...	320.1	157.3	13.5	0.49	0.09	0.04	Decrease Bid

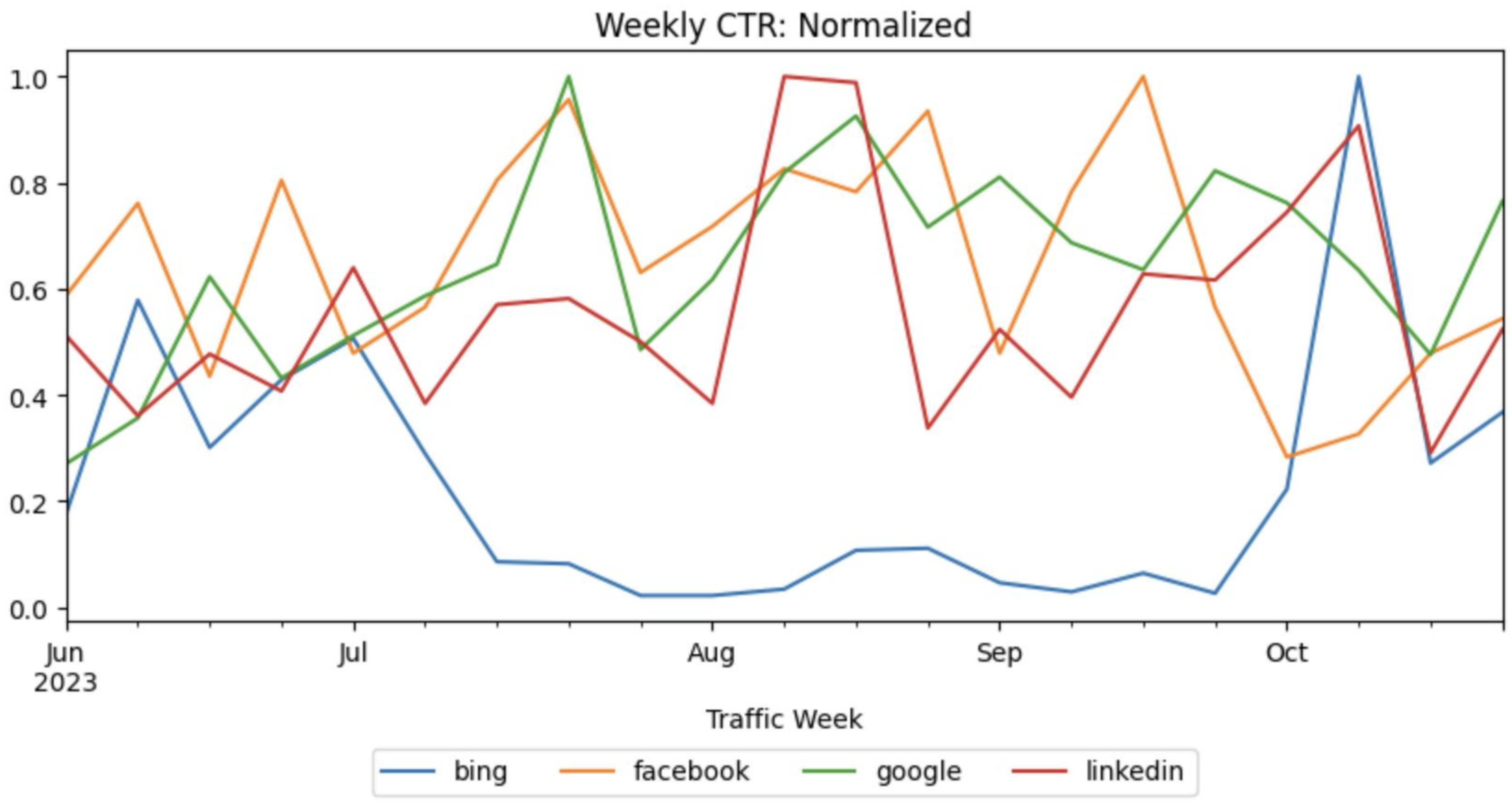
Task 2

Paid Marketing Channel Analysis

a) Paid Channel CTR Analysis

- Calculate the click-through rate (CTR) for each of the four paid marketing channels on a weekly basis

- Visualize the CTR trends over time and identify any significant fluctuations.


Weekly CTR: Normalized
1.0
0.8
0.6
0.4
0.2
0.0
Jun
2023
Jul
Aug
Sep
Oct
Traffic Week
bing
facebook
google
linkedin

Analysis

- Non-Normalized data fails to provide clear answers

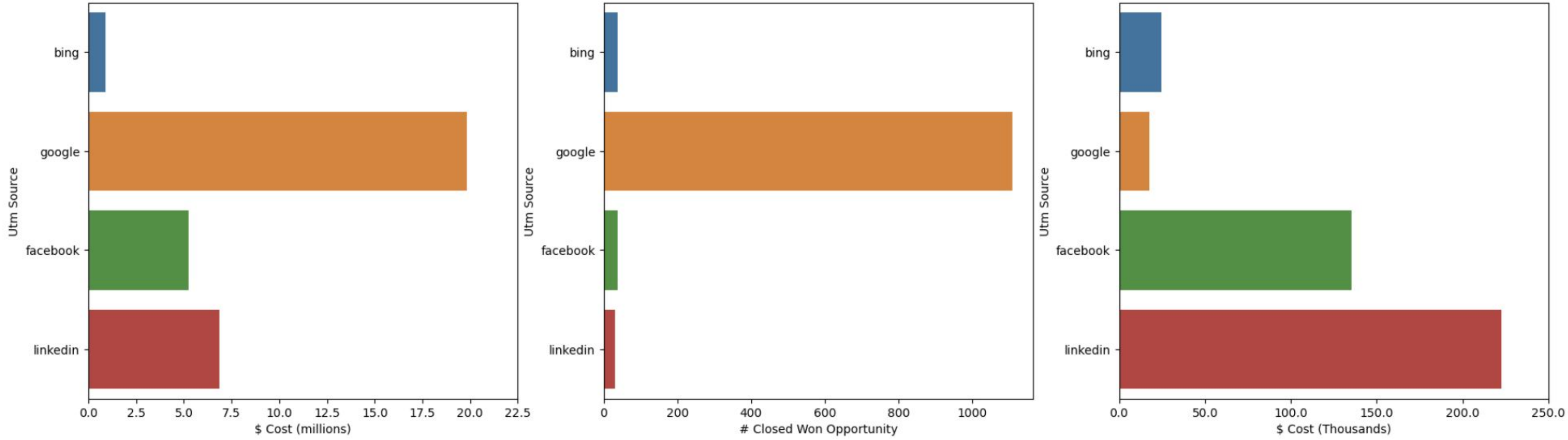
- Normalized data shows quite high fluctuations, although fluctuations don't appear unusual
  - Exception for Bing, where CTR's significantly fall mid-July before increasing at the end of September

b) Budget allocation

- Provide recommendations on how to allocate the marketing budget effectively based on the analysis of the paid marketing channels.

- Which channels should receive more budget, and which ones should be scaled back?

Aggregated KPIs per Channel



Assumptions

- Data is based on an attribution model, which fairly attributes conversions - also towards early journey channels
- Data is correct, given LinkedIn CPA is incredibly high

Recommendations

- Significantly reduce paid-social budgets (linkedin & facebook)
- Increase budgets for paid-search
  - Majority going towards 'google' given the scale opportunities over bing

c) Budget allocation: Measuring effectiveness

- How would you track and monitor the effectiveness of the revised budget allocation strategy over time?
- What key performance indicators (KPIs) would you use to measure success?

Analysis

- We need to monitor our '$ Cost', '#Cosed Won Opportunities' and 'CPA'
- Increase in efficiency, ***through a lower CPA, is the primary KPI*** to monitor here
- Monitor this metric over time, expecting a downward trend beginning once the new strategy is implemented

Additional Considerations

- Most likely the marketing strategy aims to maximise efficiency whilst maintaining a certain amount of #Closed Won Opportunity'
    - As such a ***secondary KPI to monitor would '# Closed Won Opportunity'***

General Point

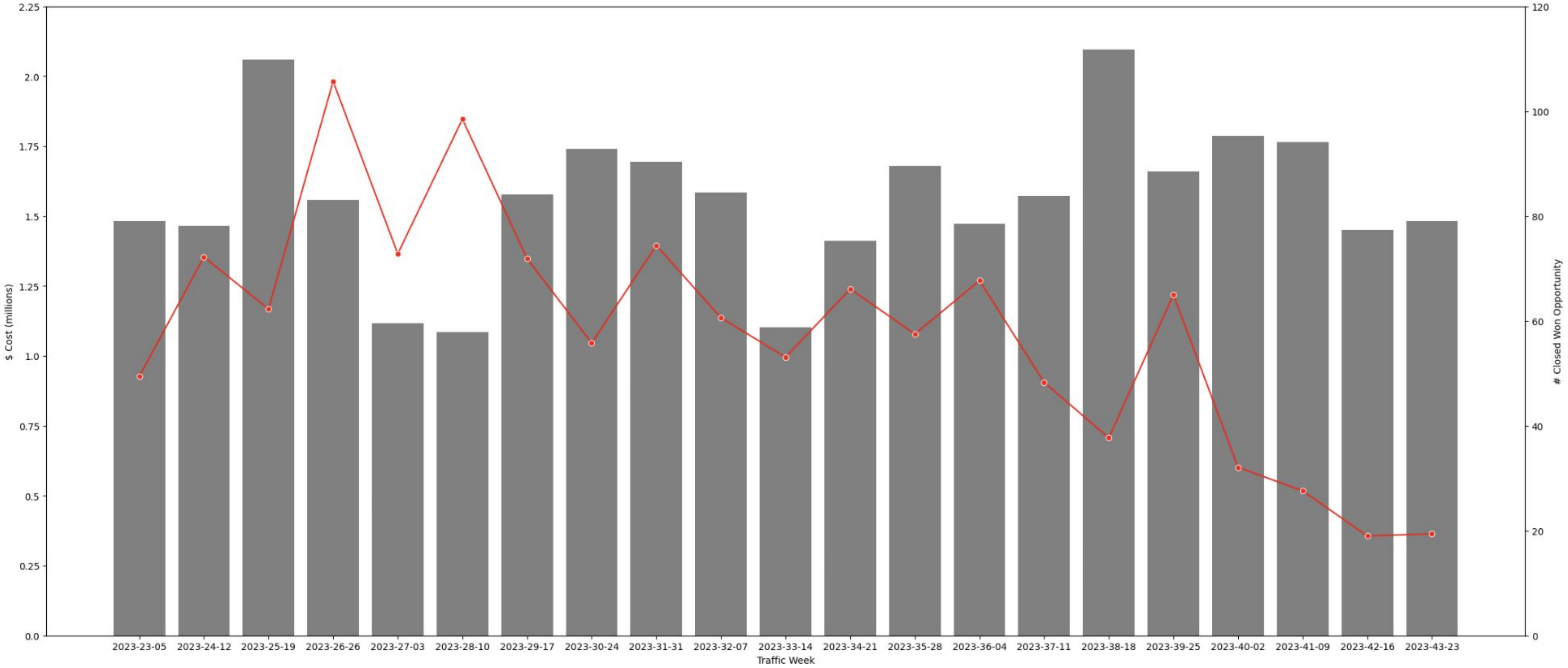
- Performance marketing typically has to consider all 3 elements (Scale, Conversions/Revenue & Efficiency)

d) Cost <> Sales Funnel Conversion Relationship

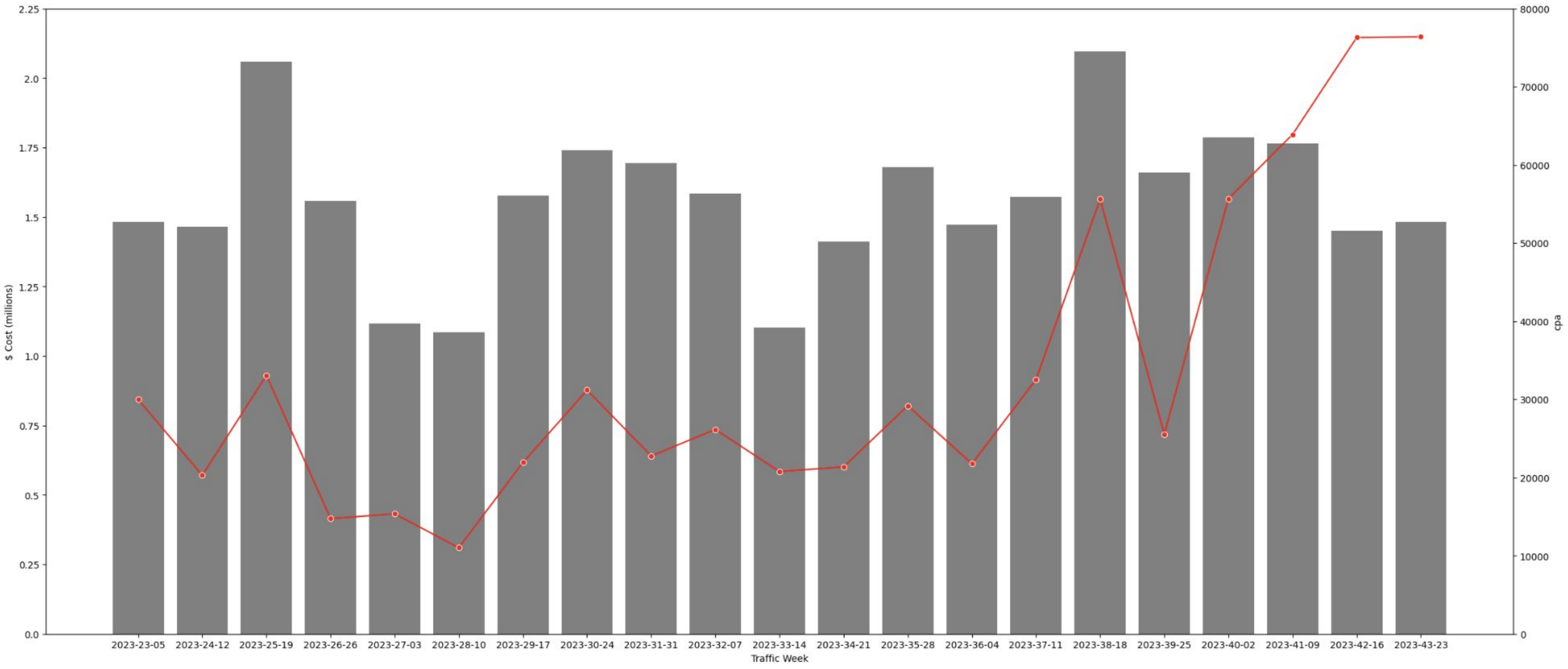
- Visualize the relationship between cost and sales funnel conversions over time

- Are there any noticeable patterns or trends?

Spend vs Closed Won Opportunities



Spend vs CPA



$ Cost (millions)
cpa
Traffic Week
2023-23-05
2023-24-12
2023-25-19
2023-26-26
2023-27-03
2023-28-10
2023-29-17
2023-30-24
2023-31-31
2023-32-07
2023-33-14
2023-34-21
2023-35-28
2023-36-04
2023-37-11
2023-38-18
2023-39-25
2023-40-02
2023-41-09
2023-42-16
2023-43-23
0.0
0.25
0.5
0.75
1.0
1.25
1.5
1.75
2.0
2.25
0
10000
20000
30000
40000
50000
60000
70000
80000

Observations

- Given that spend is stable / trending upwards, whilst Closed Won Opportunities are significantly decreasing:
    - ***CPA's are rising significantly***

- Depending on business strategy, if we want to increase our efficiency, we could consider:
    - **Decreasing spend**
    - Allocate spend towards more ***efficient channels / campaigns***

Task 3

General Questions

c) Key Takeaways

- Summarize the key takeaways and actionable recommendations from your analysis for a non-technical audience.

1. Our sales funnel data has high seasonality

- Demos / Sales Opportunities / Closed Opportunities occur Mon-Fri, not at the weekend
- Disproportionately allocate budgets to the working week

2. The beginning of the month has less activity

- Demos / Sales Opportunities / Closed Opportunities are low at the start of the month
- Allocate a larger share of the budget between the middle to the end of the month

3. Lower funnel (Sales Opportunities > Closed Opportunities) has been decreasing significantly

- Investigate underlying issues
- consider reducing marketing spend, allocating larger budgets to more active periods during the year

4. CPAs: Paid-Search > Paid-Social, Google is King

- CPAs for paid-social are extremely high, and despite the significant spend, drive few closed opportunities
- Allocate budget away from Linkedin & Facebook and paid-social (predominantly Google)
- Google, by far, has the best scale and is the most efficient channel

5. Stable spend, declining closed won opportunities = Rising CPAs

- With spend stable / moderately increasing, our lower funnel drop is leading to far fewer closed opportunities
- CPAs are rising significantly

a) Missing Values

- Are there any data quality issues or missing values in the datasets? How would you handle them if you found any?

Data Quality

Data quality appears to be *generally quite good*, despite some issues and unusual observations:

1. There are some ***formatting issues***, which need to be dealt with, in order to work with the data:
- Cost data isn't numerical
- Date's aren't always datetime format

2. Null Values:
- Beyond the Utm Campaign, there are no null values in the entire dataset

3. Bing CTR:
- CTR drop is so significant that it would require an investigation in click / impressions to ensure the data is accurate

4. Linkedin CPA
- Intuitively the value seems much too high

Dealing with missing values

Can have significant impact on our analysis and therefore needs to be dealt with. Some solutions:

1. **Drop missing / null values**

2. **Replace missing / null values with an average**
    - More sophisticated might be replacing with the forecasted trend (Can be overkill in many situations)

b) Outliers

- How would you handle outliers in the data? Are there any outliers in the provided datasets?

Zscore (Normal Distributions)

- Common approach to deal with outliers is using a zscore, which calculates the standard deviation from mean, for each value
- Essentially, we calculate how far each value is from the average
- Assuming the data follows a normal distribution, we would deem zscores greater than 3, as extreme outliers

Excluding outliers

- Based on the zscore the majority of outliers are from google
- Given that google, by far, is the best performing channel, these values are probably not outliers which we should remove
- Removing these values would, incorrectly, distort the entire analysis

Notes

- This is assumes the data is normally distributed, which was not tested in this analysis
- One consideration was to calculate a zscore, within each UTM source, which most likely would have kept all of the Google outliers. This wasn't done due to time constraints
- There are additional approaches to dealing with outliers, that weren't considered due to time constraints

c) Attribution models

- How would you describe how marketing attribution models work? Note: this is a general question, not related to Deel or the dataset you have worked on for this task

General

- An attribution model is the set of rules which determines how much each conversion / revenue should be allocated towards each step within the conversion path

Marketing Context

- Within a marketing context, an attribution model ensures that each marketing channel with which a user has engaged with, get's it's according share of the final conversion / revenue

Attribution Models [1 / 2]

First / Last Touch

- Attributing the conversion/revenue to the first/last marketing channel within the conversion journey
- Comes with significant limitations

Linear

- Here we assign each step within the conversion journey an equal share

Bathtub Attribution

- Assign the first and last touch each 40%, attributing the remaining 20% on the steps in between the first and last touch
- When there are 2 steps, each is attributed 50%
- Significant improvement on first/last/linear models in that it incorporates larger weighting to the driving initial / closing touchpoints, whilst ensuring the touchpoints in between are accounted for.

Attribution Models [2 / 2]

Probabilistic Attribution Modelling

- Given the move away from App Tracking and Cookies, it is getting increasingly difficult to identify users across their conversion journeys.

- Probabilistic attribution is a form of attribution modelling based on probabilities, rather than user identifiers. Machine learning and statistical modelling techniques are used to identify probable conversions across various marketing touchpoints.

- There is a significantly more complexity in both setup, maintenance and interpretation for non-technical stakeholders

c) Attribution model proposal

- What attribution model do you propose for our business?

Primary: Probabilistic Attribution Modelling

- Given the resources available at Deel, there would be value in having a probabilistic attribution model which relies on Machine Learning and statistical modelling
- Not only does this deal with the issue regarding the move away from cookies, but can also incorporate out-of-home advertising, in-person events and TV in a way that a classic user identifier model cannot.

Secondary: Bathtub Attribution

- If this isn't possible, Deel should incorporate a Bathtub Attribution model, based on server-side tracking, to minimise the impact away from cookies