# GROUP PROJECT PLAN

# RESILIENT FORECASTING: ENHANCING ELECTRICITY DEMAND MODELS FOR CLIMATE EXTREMES

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# Abstract

This project aims to investigate the impact of extreme temperatures on the accuracy of electricity demand forecasting in the region of New South Wales, Australia. Although the relationship between temperature and electricity demand is established, less emphasis has been placed on how the extremity of temperatures (extremely high or low temperatures) can affect the accuracy of electricity demand forecasting. Using historical data from the Bankstown region, we will first conduct exploratory analysis to identify patterns of forecast bias across temperature ranges. We will then develop machine learning models to improve prediction accuracy during extreme weather conditions. The findings aim to support more resilient forecasting systems and inform decision-making for energy providers facing increasing climate variability.

# Contents

# 1 Introduction & Motivation

Electricity demand forecasting is vital to ensure operational efficiency as accurate forecasting can help maintain grid stability, allow for generation planning and also improve cost efficiency.

This project is in partnership with Endgame Economics, whom are a consulting firm based in Sydney and specialise in economic modelling for the energy sector. The question formulated as the main focus of this study is "Do extreme temperatures (unusually high or low daily temperatures) lead to significant errors in electricity demand forecasts for NSW?" By analysing historical demand and temperature data in Bankstown, we will be able to gather valuable insights as to whether forecast errors increase in extremities of hot/cold.

We will conduct a two-stage analysis. First, exploratory data analysis will be used to clean and visualise patterns of forecast bias across temperature ranges. Second, predictive models (including multiple linear regression, random forest, and gradient-boosted trees) will be developed to improve accuracy on extreme weather days, potentially incorporating additional data of humidity and rainfall. This approach balances intuitive exploration with statistical validation.

This research is motivated by both practical and strategic concerns. As climate change drives more frequent and severe temperature extremes, electricity demand becomes harder to predict. If these conditions significantly degrade forecast accuracy, energy providers will need to adapt their predictive tools to remain reliable. Our findings aim to support more resilient forecasting systems and better decision-making.

# 2 Brief Literature Review

In their FY 2026 Corporate Strategic Plan, the Australian Energy Market Operator (AEMO) identified electricity demand forecasting as a key priority for effective operational performance [1]. Inaccurate demand forecasts can lead to overloading or power outages, resulting in significant financial penalties for operators, as well as increased market volatility due to uncertainty in the supply-demand balance [2]. This suggests that accuracy is an important metric to optimise when developing electricity demand forecast models.

Many types of models have been developed or implemented in electricity demand forecasting, each with their own advantages and limitations [3]. The most straightforward method used in electricity demand forecasting models is Multiple Linear Regression (MLR). MLR has proven to be effective in many prediction applications, has a relatively fast running speed, and does not require extensive computer resources [4]. Liu and Lee [5], implemented an MLR model to estimate annual electricity and energy consumption in the UK using economic and meteorological explanatory variables. The authors used root mean square error (RMSE), mean absolute percentage error (MAPE), and maximum error as performance metrics, and compared the results to other predictive models, including a back-propagation neural network and least square support vector machine [5]. The study identified MLR as the weakest performer, likely due to its simplistic structure leading to overestimation in test predictions [5]. Similarly, other studies have found that MLR models, despite being adequate for electricity demand forecasting, can have limitations when nonlinear dynamics emerge [6, 4], and in their capacity to extract and learn from patterns in historical consumption data [7]. Given the non-linearity of temperature response functions [8], relying solely on an MLR model for electricity demand forecasting presents a clear methodological gap and as such MLR models should be compared to alternatives to ensure optimal accuracy is achieved. Patney and Patel [9] offer the alternative method of ensemble learning, in particular Random Forest (RF) and Gradient Boosted Trees (GBTs), to improve model accuracy and robustness in electricity demand forecasting. Both rely on decision trees: RF builds multiple trees in parallel and averages predictions, while GBTs construct trees sequentially to correct prior errors [10]. Patney and Patel [9] compared RF and GBTs (XGBoost, LightGBM) to non-ensemble algorithms including, Ordinary Least Squares, LASSO, Least Angle Regression, Ridge and Bayesian Ridge for electricity demand forecasts. Based on MAPE, RMSE, mean absolute error (MAE) and sum of squared errors (SSE), the authors concluded that the best performing models for accuracy and computational efficiency were RF and LightGBM, however, also noted the extensive tuning of hyperparameters required for both models to achieve optimal accuracy [9]. Baker et al [11] demonstrated the effectiveness of an XGBoost model when forecasting electricity consumption in the presence of noise and highlighted the importance of cross-validation in evaluating model robustness. RF models have also been shown to perform well with outliers [4]. These findings suggest that RF and GBTs may be good candidates for improving forecast accuracy at temperature extremes.

As in the case of model selection, researchers have used various input variables to accurately predict electricity demand, including temperature, relative humidity and rainfall [12, 13, 14, 15, 7]. It has been established that of these climatic variables, temperature is the most important [15, 8] and as such should be considered for use in any electricity demand forecasting model. Socio-economic factors such as population, GDP and electricity price have also been incorporated in forecasting models [6, 16, 5]. Although socio-economic variables are considered outside the scope of this project, they could be considered for further model refinement in the future.

## 3 Methods, Software & Data

### *3.1 Methods*

Our analysis will focus on whether "extreme" temperature days (unusually high or low maximum daily temperatures) lead to larger errors in electricity demand forecasts for NSW. It will comprise two parts: (A) exploratory analysis and (B) model-based investigation.

*A. Exploratory analysis*

Using Python to clean and integrate the datasets, we will produce scatterplots, quadratic/LOESS fits, and error-binned histograms to evaluate patterns of forecast bias across different temperature ranges. This will first be applied to the existing historical forecast dataset provided, and then repeated on our own model outputs to assess whether the new models reduce errors on extreme weather days.

*B. Model-based investigation*

We will first establish a baseline using the existing historical forecast dataset. Then we will produce new model forecasts based on historical weather data, enriched with additional features such as humidity and rainfall, to test whether forecast accuracy can be improved on extreme weather days. For this, we will attempt to implement two machine learning forecasting methods alongside the historical forecast benchmark. Candidate methods include:

- **Multiple Linear Regression**: captures linear relationships between demand, temperature, and enriched weather features.
- **Random Forest Regression**: captures more complex, nonlinear patterns, and may show improved accuracy on extreme weather days.
- **Gradient Boosted Trees**: an advanced tree-based method that builds many small models (an ensemble) to improve accuracy, especially when demand changes sharply.

Models will be trained on historical data using rolling-window cross-validation, with performance benchmarked against each other and baseline forecasts.

### *3.2 Software*

- Group meetings: Microsoft 365 Teams
- Collaboration: GitHub (version control), Trello (task tracking), OneDrive (file sharing)
- Data analysis and modelling: Python (`pandas`, `numpy`, `scikit-learn`, `XGBoost`, `matplotlib`)
- Reporting and Presentation: Overleaf and Microsoft Powerpoint

### *3.3 Data*

We will primarily use the datasets provided to us:

- **Actual demand**: 5-minute resolution electricity demand for NSW.
- **Forecast demand**: half-hourly forecasts with timestamped issue times.
- **Temperature**: half-hourly observations across NSW.

To enrich these, we plan to incorporate publicly available Bureau of Meteorology (BOM) datasets, particularly daily humidity and rainfall records (https://www.bom.gov.au/climate/data/). These additional weather variables may help explain residual error on extreme temperature days and improve model forecasts.

## 4 Team Roles & Responsibilities

To support effective role allocation, each member created a personal mind map of their skills and expertise (Section 6). These informed the assignments summarised in Table 1.1.

| **Team Member** | **Assigned Role** |
|---|---|
| Liam Dobson | Team Lead |
| Elizabeth Muirhead | Research Lead |
| Adil Ali | Data & Visualisation Lead |
| Thomas Frank | Model Lead |

Table 1.1: Team Roles and Responsibilities

### *4.1 Team Lead*

Drawing on his professional experience as a lead consultant, Liam was appointed Team Lead. He is responsible for coordinating project activities, planning tasks, and monitoring progress across contributors.

### *4.2 Research Lead*

Elizabeth's academic background equips her with a strong foundation for engaging with scientific literature, particularly in areas related to temperature and energy forecasting. As Research Lead, she will identify relevant scholarly sources, synthesise key findings, and translate these insights into design considerations.

### *4.3 Data & Visualisation Lead*

With prior experience in performance marketing analysis and large-scale data management, Adil was appointed Data & Visualisation Lead. His responsibilities include cleaning and interpreting the primary dataset, sourcing and pre-processing supplementary data, and producing visualisation aids to support modelling, and reporting efforts.

### *4.4 Model Lead*

Thomas was selected as Model Lead for his technical proficiency in Python and machine learning. His expertise spans multiple predictive techniques, including multiple linear regression, random forest regression, and gradient-boosted trees, as well as supervised and unsupervised learning. He will lead the development, calibration, and evaluation of the team's forecasting models.

## 5 Activities & Schedule

To facilitate effective project planning and timeline management, a Gantt chart was developed to visualise the scheduled activities assigned to each team role. The timeline incorporates weekly team syncs and regular consultations with the lecturer to ensure ongoing alignment and progress tracking. Key milestones and submission deadlines are also included and are illustrated in the Gantt chart on the following page.

# DATA SCIENCE PROJECT

**Group C**

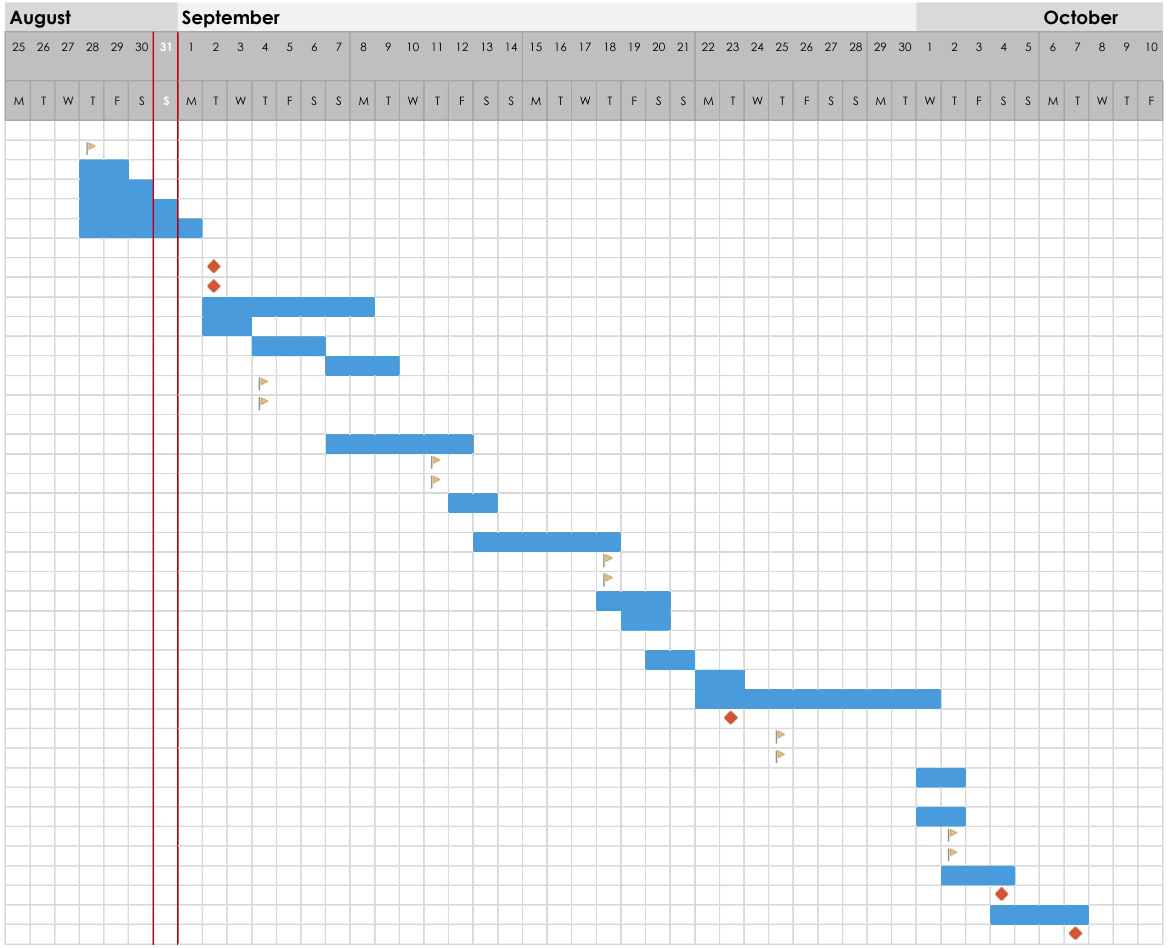
**Adil, Elizabeth, Liam, and Thomas**

Project start date: 25/8/2025

Scrolling increment: 0

Legend: On track | Low risk | Med risk | High risk | Unassigned

| Milestone description | Category | Assignee | Start | Days |
|---|---|---|---|---|
| **Week 1** | | | | |
| Team Kick-off Meeting | Meeting | All | 28/8/2025 | 1 |
| Set up shared workspaces | Low Risk | Team Lead | 28/8/2025 | 2 |
| Initial Data Exploratory Work | Low Risk | Data + Model Leads | 28/8/2025 | 3 |
| Plan Project (Inc. activities, software, team roles) | Low Risk | Team Lead | 28/8/2025 | 4 |
| Prelim Literature Review | Low Risk | Research Lead | 28/8/2025 | 5 |
| **Week 2** | | | | |
| Assessment 1 Group Project Plan - Part A | Deadline | All | 2/9/2025 | 1 |
| Assessment 1 Group Project Plan - Part B | Deadline | All | 2/9/2025 | 1 |
| Cont. Literature Review | Low Risk | Research Lead | 2/9/2025 | 7 |
| Audit available datasets (energy, temperature) | Low Risk | Data Lead | 2/9/2025 | 2 |
| Conduct exploratoration on available data (EDA) | Low Risk | Model Lead | 4/9/2025 | 3 |
| Identify and source external data | Low Risk | Research + Data Leads | 7/9/2025 | 3 |
| Weekly Consultation w/ Ziyang Lyu | Meeting | All | 4/9/2025 | 1 |
| Group C Weekly Check In | Meeting | All | 4/9/2025 | 1 |
| **Week 3** | | | | |
| Build baseline forecasting model(s) | Low Risk | Model Lead | 7/9/2025 | 6 |
| Weekly Consultation w/ Ziyang Lyu | Meeting | All | 11/9/2025 | 1 |
| Group C Weekly Check In | Meeting | Research + Data Leads | 11/9/2025 | 1 |
| Test baseline model accuracy | Low Risk | Model Lead | 12/9/2025 | 2 |
| **Week 4** | | | | |
| Build enhanced models w/ auxilary data | Low Risk | Model + Data Leads | 13/9/2025 | 6 |
| Weekly Consultation w/ Ziyang Lyu | Meeting | All | 18/9/2025 | 1 |
| Group C Weekly Check In | Meeting | All | 18/9/2025 | 1 |
| Test enhanced forecasting model accuracy | Low Risk | Model + Data Leads | 18/9/2025 | 3 |
| Compare baseline vs enhanced models | Low Risk | Model + Data Leads | 19/9/2025 | 2 |
| **Week 5** | | | | |
| Refine models based on feedback | Low Risk | Model Lead | 20/9/2025 | 2 |
| Finalize visualisations and results | Low Risk | Data Lead | 22/9/2025 | 2 |
| Drafting report | Low Risk | Team Lead | 22/9/2025 | 10 |
| Assessment 2: Individual reflective portfolio | Deadline | All | 23/9/2025 | 1 |
| Weekly Consultation w/ Ziyang Lyu | Meeting | All | 25/9/2025 | 1 |
| Group C Weekly Check In | Meeting | All | 25/9/2025 | 1 |
| Peer review of report first draft | Low Risk | All | 1/10/2025 | 2 |
| **Week 6** | | | | |
| Draft Video Presentation | Low Risk | Team Lead | 1/10/2025 | 2 |
| Weekly Consultation w/ Ziyang Lyu | Meeting | All | 2/10/2025 | 1 |
| Group C Weekly Check In | Meeting | All | 2/10/2025 | 1 |
| Finalise report | Low Risk | All | 2/10/2025 | 3 |
| Assessment 3: Group project report | Deadline | All | 4/10/2025 | 1 |
| Finalise Video Presentation | Low Risk | All | 4/10/2025 | 4 |
| Assessment 4: Group video presentation | Deadline | All | 7/10/2025 | 1 |



# 6 Individual Mind Maps

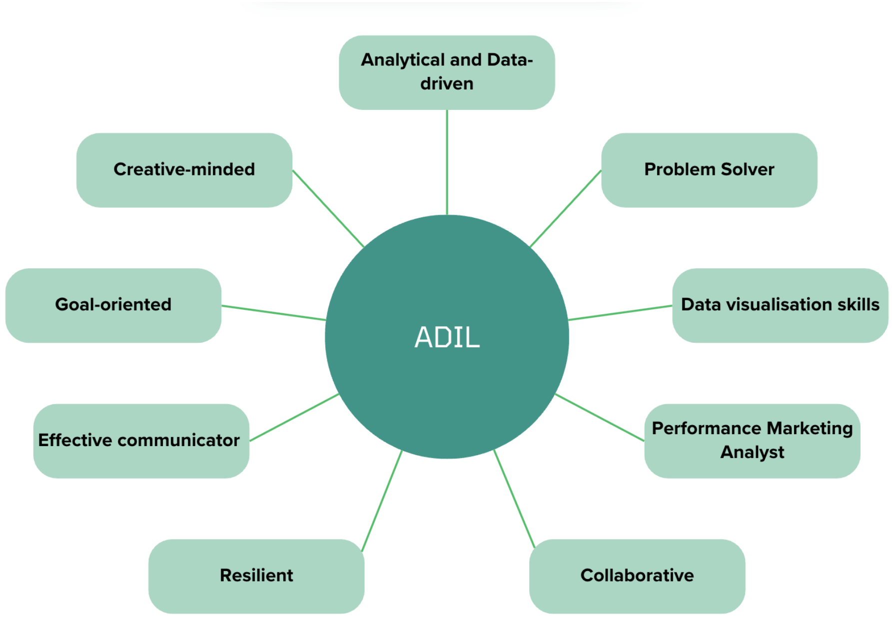



Figure 1.1: Adil's Skill Mind Map

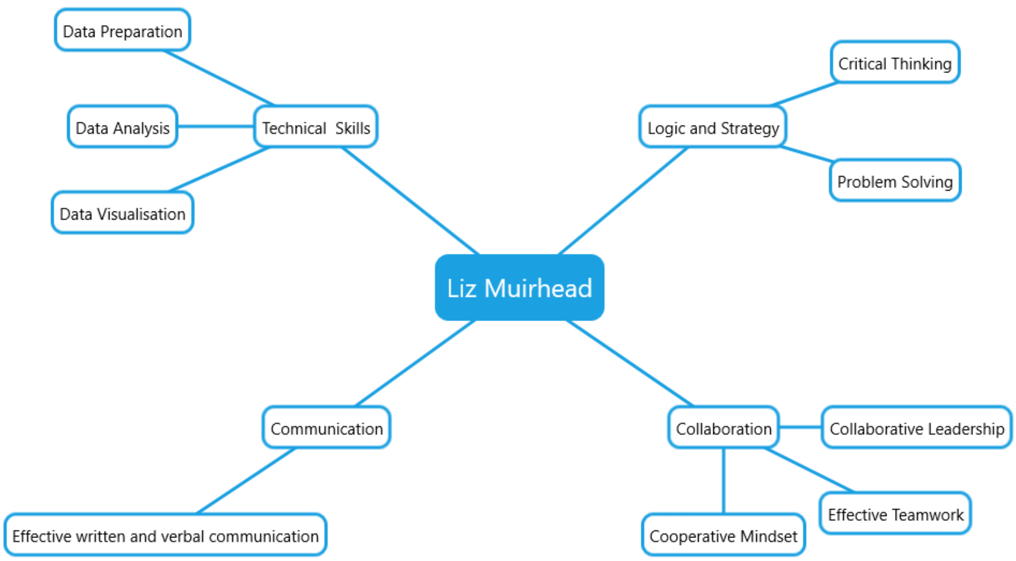



Figure 1.2: Elizabeth's Skill Mind Map

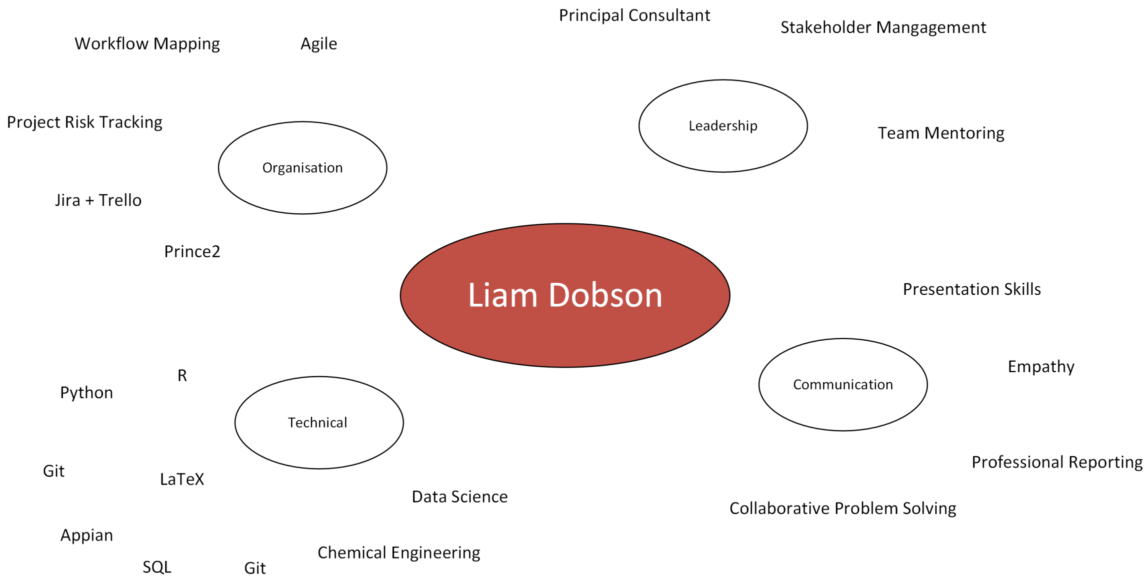



Figure 1.3: Liam's Skill Mind Map

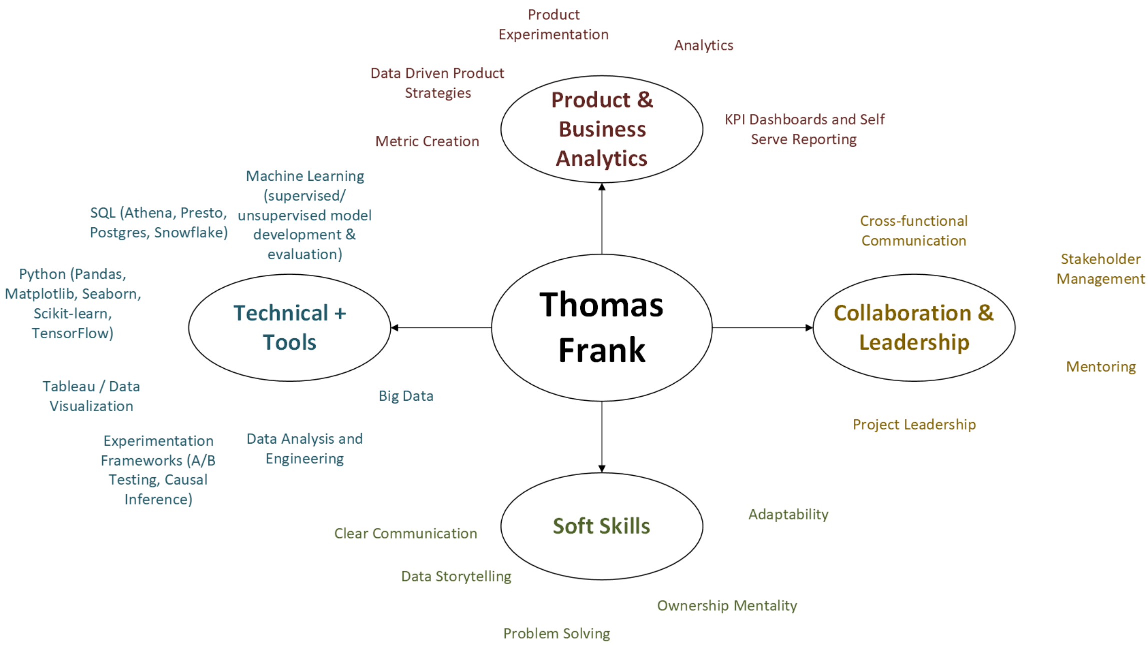



Figure 1.4: Thomas' Skill Mind Map

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