Job Recommendation Engine for Seek

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Contents

1. Background

Australia's online recruitment platform in thriving[1].

- Market size: 0.9 billion AUD
- Annual growth rate: 8.4%

Seek is one of the biggest online job marketplaces, aiming to connect more people to relevant employment.

To realize this ambition, Seek is building a job recommendation engine to increase the view and application rates of the jobs[2].

This presentation will introduce the design, develop of a job recommendation engine.

Reference:
1. *https://www.ibisworld.com/australia/industry/online-recruitment-services/4049/*
2. *https://talent.seek.com.au/products/jobads*

2. Data Preprocessing and Analysis

2.1.1 Raw Data Preprossing: Job Advertisement Overview

This dataset is the job description for jobs posted on Seek.

It contains 50k records in json format. **No duplication** but **has missing data** for some fields.

Data Drop logic

- Row removal:
    - Jobs (372 records) with **non-English** description are removed to avoid negative effect during text analysis.
- Column removal:
    - Column *location*, *suburb*, *area* are dropped **after address logic**.
    - *bullet 1, bullet 2, bullet 3* are dropped due to **too many missing data** and no way to fill in blanks.

2.1.1 Raw Data Preprossing: Job Advertisement Columns

Cleaned and Processed table:

Column	Data Type	Comment	Action
id	String	PK for each job	
cleaned_title	String	Job name	Remove meaningless words from title
abstract_content	String	Description	Combine abstract and content, remove meaningless words
classification	String	Industry	
sub_classification	String	Sub -Industry	
work_type	string	Work types	

2.1.1 Raw Data Preprossing: Job Advertisement Columns

To continue:

Column	Data Type	Comment	Action
latitude	float (64)		Obtain coordinates and full addresses from 3rd API based on location info
longitude	float (64)		
region_code	integer(64)	A flag to distinguish Australian and non-Australian address *(0 - AU, 1- NZ, 999-Others)*	
country	string	Country name	
state	string	State name for Australian address	
salary_unit	String	Salary unit(hour, week, month, year)	Extract from additionalSalaryText
salary_value	Float(64)		

2.1.1 Raw Data Preprossing: Parsing locations in Job Advertisement

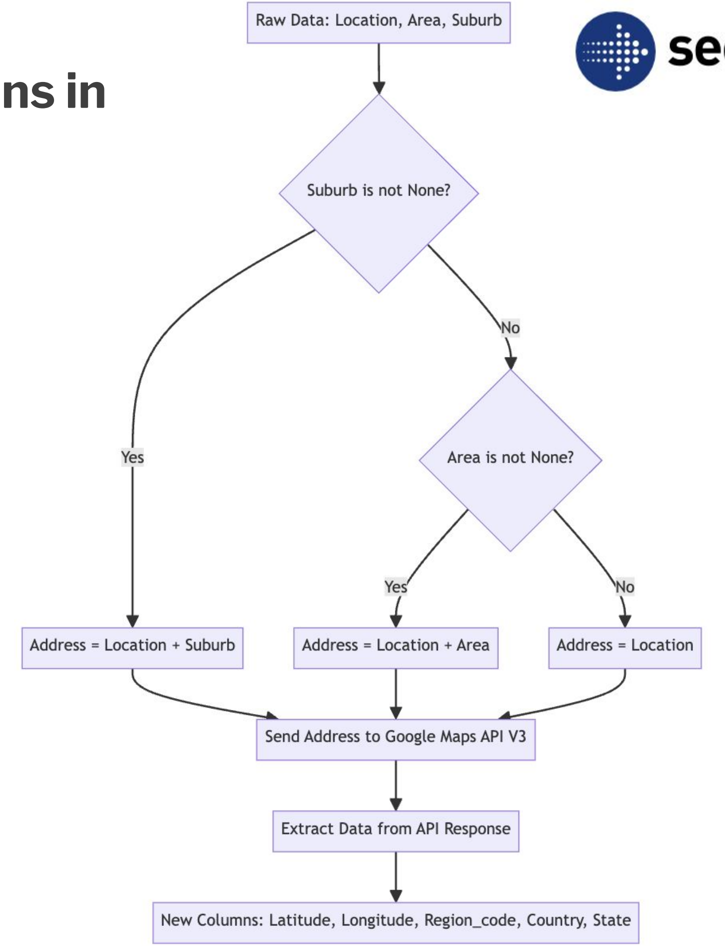
The logic of new geographical columns:

Location is always not None.

```
If suburb is not None,
      address = concat(location, suburb)
else if area is not None,
      address = concat(location, area)
else address = location
```

Address is then put into the Google Map API to generate the new columns:

- Latitude
- Longtitude
- Region_code
- Country
- State



2.1.1 Raw Data Preprossing: Parsing Salary in Job Advertisement

Parsing the *additionalSalaryText* in the original dataset.

Apply **Regex** rules to extract **salary unit** and **salary amount**.
Available salary unit: Hourly, Daily, Weekly, Monthly, Annually

For a salary range, use the average of the range.

Leave a placeholder ‘NA’ in case the salary is not available.

additionalSalaryText	Salary Unit	Salary Amount
$140k + Car Park - Call James Calleja	Annually	140000
$110k - $120k p.a. + Numerous Perks!	Annually	115000
$30 - $34.99 per hour	Hourly	32.50
Base + Super + Uncapped Commission	NA	0

2.1.2 Raw Data Preprossing: Job Event Overview and Columns

This dataset is the event job triggered every time resume (candidate) view or apply for a job. It originally contain 4.3M records in csv format. After **deduplication**, it keeps 1.4M records

Cleaned and Processed table:

Column	Data Type	Comment	Action
event_datetime	String	Timestamp for each log	No need
resume_id	String	Identify who triggered the log	
job_id	String	Join key for Job Ads Table	
event_platform	String	ios, Andriod, web	
kind	String	V - View, A - Apply	

2.1.3 Raw Data Preprossing: Join two datasets

The new dataset combines Job Event with Job Advertisement, **joined** through “**id**” from Job Advertisement and “**job_id**” from Job Event, with **1.4M records** in total.

Except for the columns from both tables, additional columns are added to enrich applicant profile.

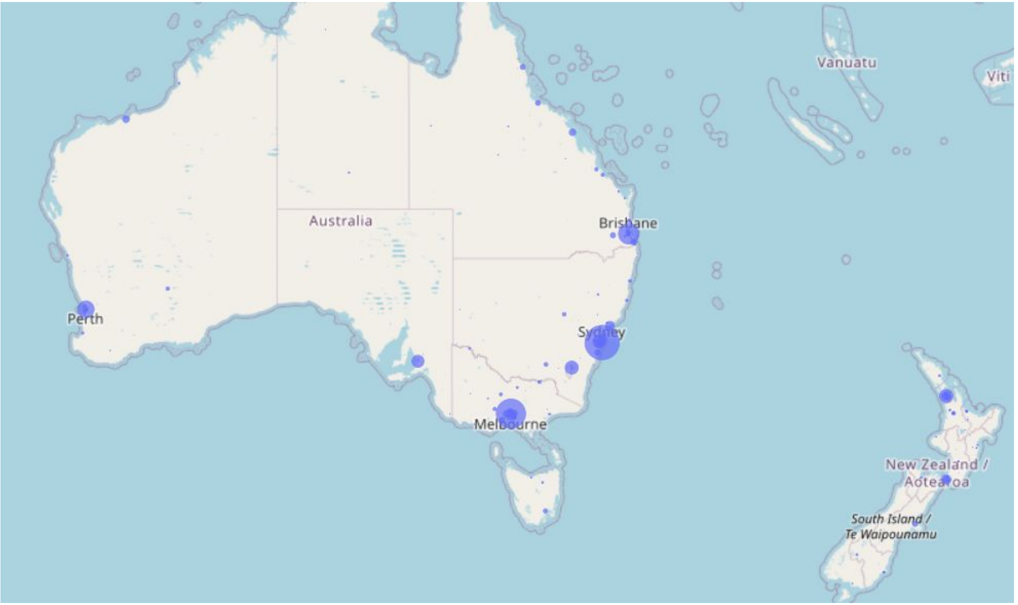
Additional Column	Data Type	Comment	Action
centroid_longitude	Float(64)	Assume location of each applicant	Calculate the averaged coordinates for all jobs each candidate interacted with, based on training set
centroid_latitude	Float(64)		
farthest_distance_to_center_km	Float(64)	Farthest distance for all jobs viewed/applied by each applicant	Calculate the maximum distance between each candidate and jobs
shortest_distance_to_center_km	Float(64)	Shortest distance for all jobs viewed/applied by each applicant	Calculate the minimum distance between each candidate and jobs

2.1.3 Raw Data Preprossing: Join two datasets

To continue:

Column	Data Type	Comment	Action
average_distance_to_center_km	Float(64)	Averaged distance for all jobs viewed/applied by each applicant	Calculate the average distance between each candidate and jobs
title_keywords	String	Keywords for titles	Get keywords for each job based on classification based TF-IDFmatrixes
abstract_content_keywords	String	Keywords for abstract_content	Get keywords for each job based on classification based TF-IDFmatrixes

2.2.1 EDA: Job Density Map across Australia and New Zealand

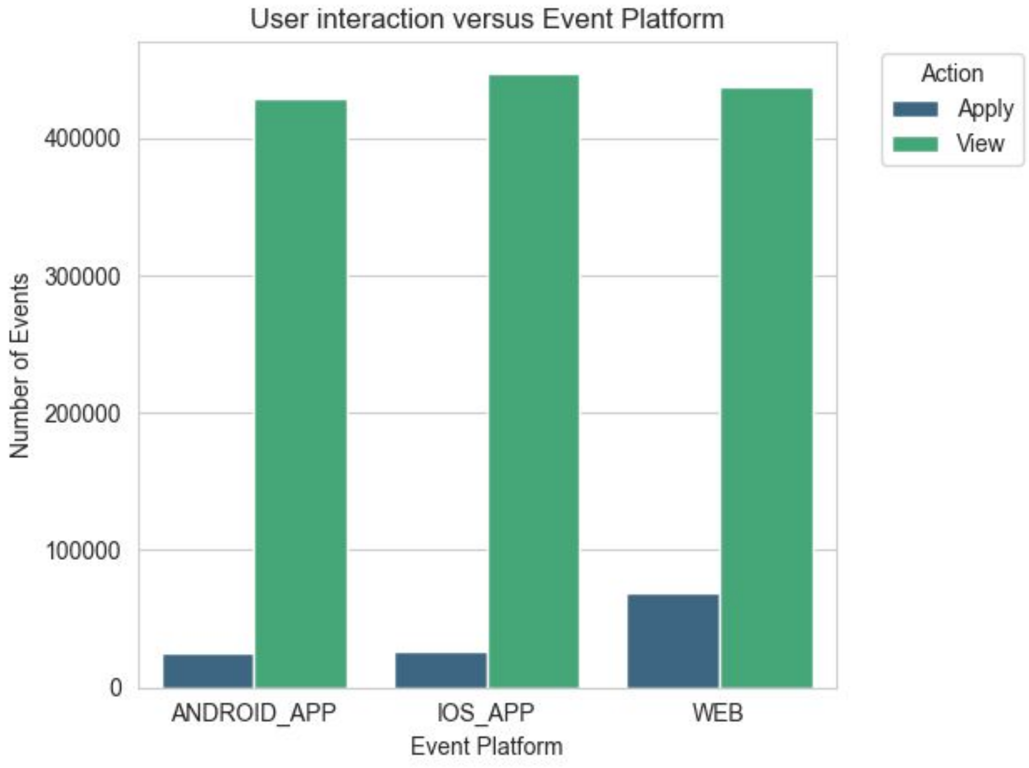


Most job opportunities are from the **capital city** of each state.

Sydney has the most job opportunities, followed by Melbourne and Brisbane.

The amount of jobs from other cities are even fewer than that from NZ cities.

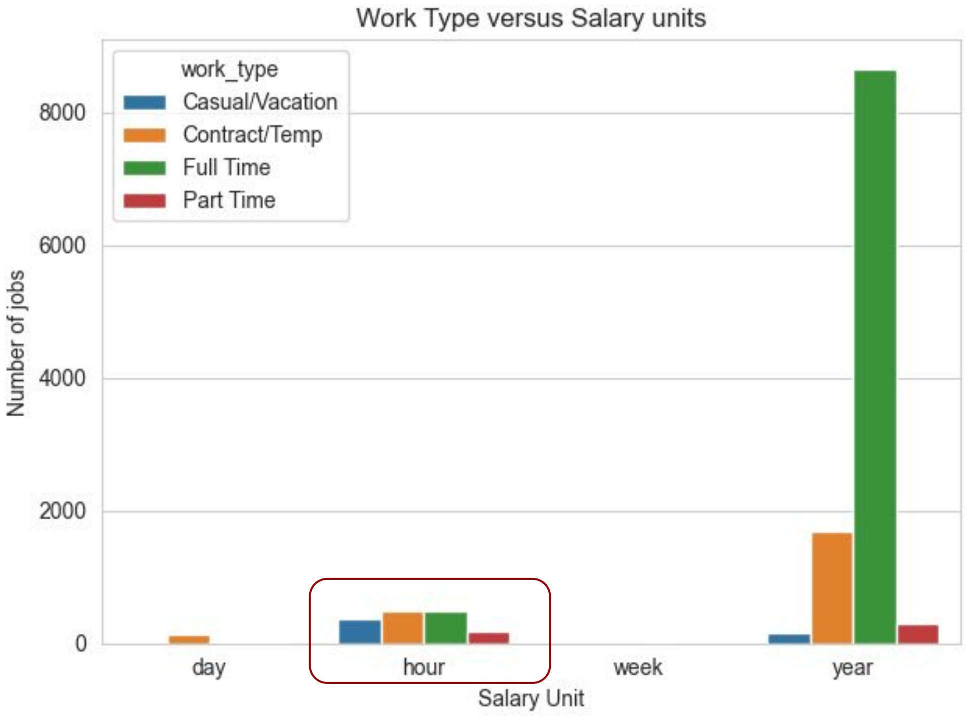
2.2.2 EDA: User Interaction vs Platform



Almost no difference between Andriod and iOS.

The conversion rate (VIEW to APPLY) from mobile platforms (Android/iOS) is 50% less than that from the web.

2.2.3 EDA: Work Type vs Salary Unit

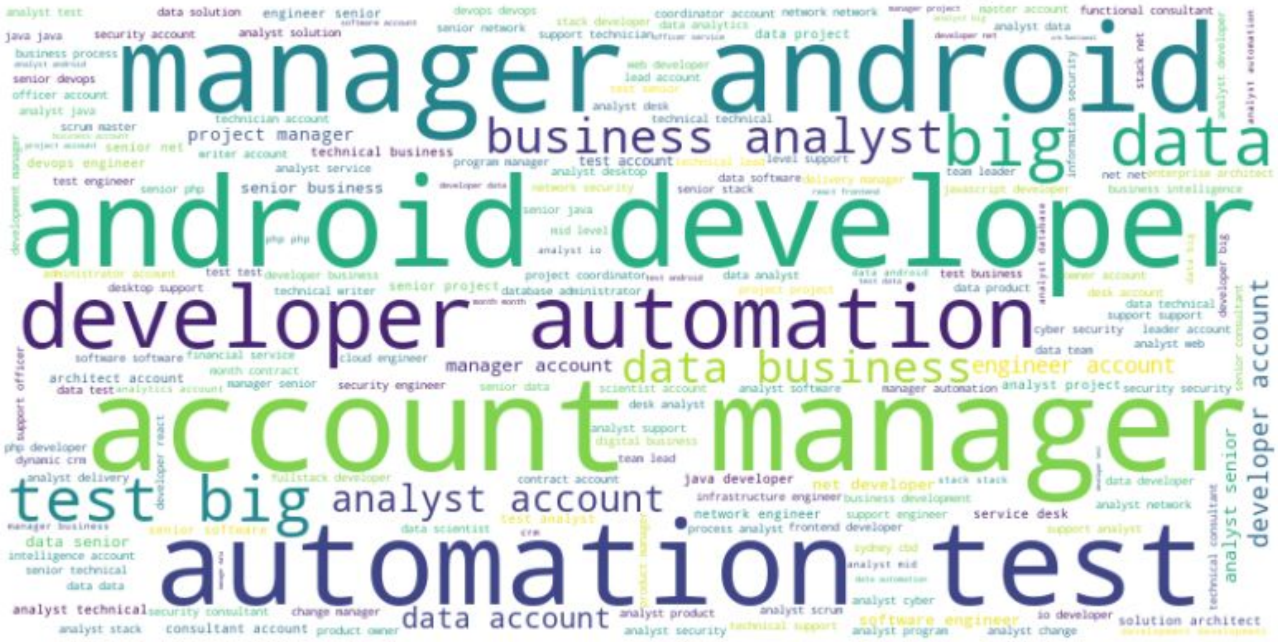


Most full-time jobs are annual salary, which makes sense.

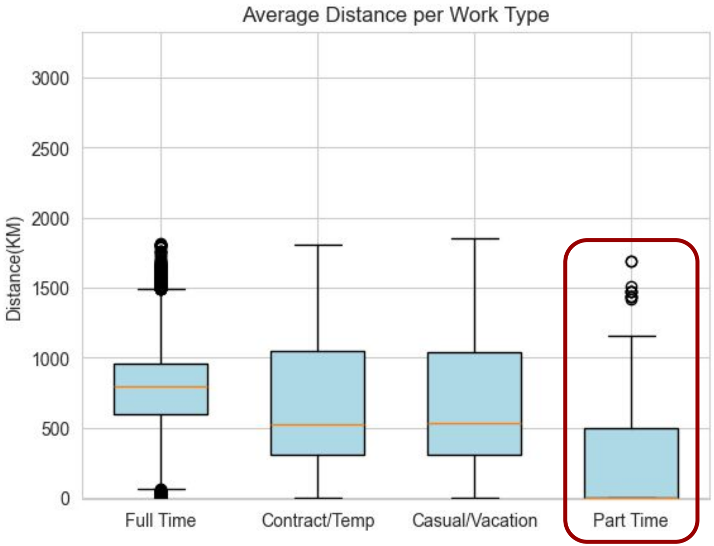
However some full-time jobs are hourly salary, which might be errors in the raw data.


```
{'additionalSalaryText':
      'Up to $55 per hour',
'classification':
      {'name': 'Healthcare & Medical'},
'subClassification':
      {'name': 'Medical Imaging'},
'location':
      {'name':'Rockhampton'},
'workType':
      {'name': 'Full Time'}
}
```

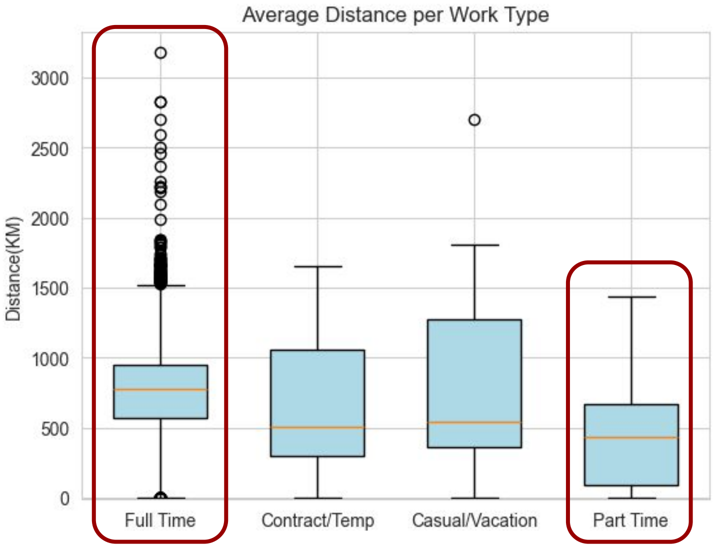
2.2.4 EDA: Word Cloud for ICT job titles



2.2.5 EDA: Avg Travel Distance vs Work Type



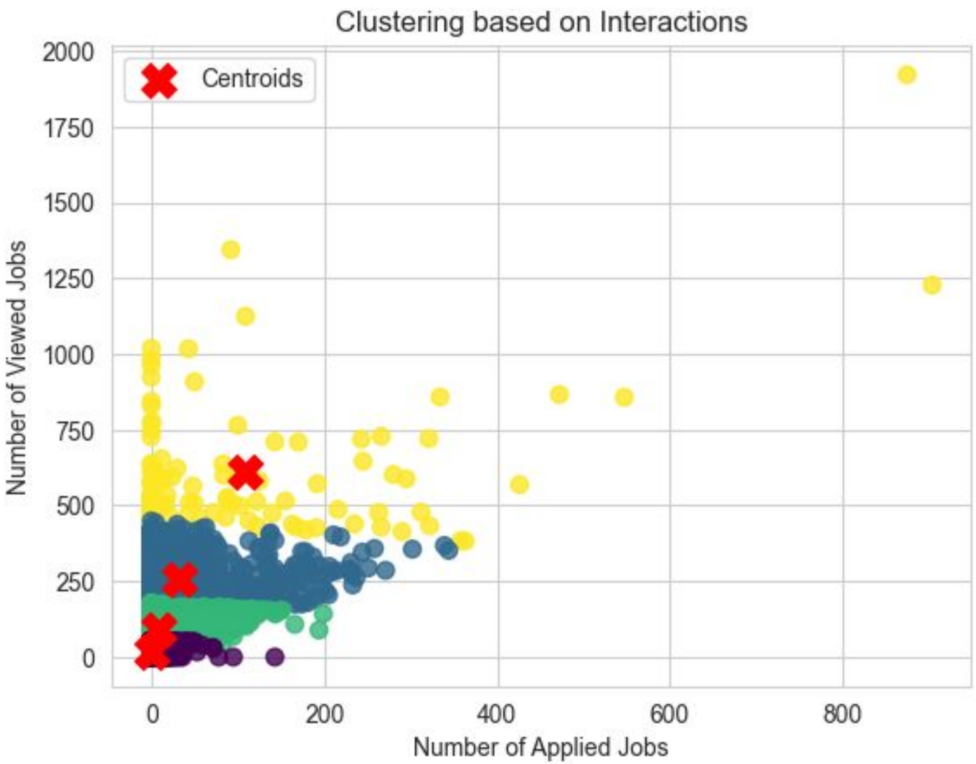
View



Apply

No significant difference of the avg. accepted distance across all work types for APPLY.

2.2.6 EDA: Applicant Interaction Clustering



Applicants are clustered into **4 groups**.

Group 1: **Explorer**. Casually browsing, or just keeping an eye on the market.

Group 2: **Opportunist**. Actively looking for the right opportunity but are cautious.

Group 3: **Power Seeker**. Highly motivated, aggressively pursuing new opportunities.

Group 4: Probably **bot**. Unreasonable amount of views and applies.

3. Use Cases

3.1 Boosting Engagement & Conversions with Dual-Layer AI Predictions

Problem Statement

- **Low Email Effectiveness**
  - Subscription emails fail to re-engage inactive users, resulting in declining view rates.
  - Example: Only 15% of users open non-personalized job alerts.
- **Inefficient Recommendations**
  - Users click emailed job links but rarely apply due to mismatch.
  - Example: 70% of clicks do not convert to applications.
- **Retention Risks**
  - Declining user activity harms long-term growth and revenue.

Assumption

- The jobs that applicants view or apply for are typically concentrated around their geographical location. So, an applicant's location is determined by calculating the **geographic centre** (centroid) of all the **job locations they have interacted with**, whether viewed or applied.

3.1 Boosting Engagement & Conversions with Dual-Layer AI Predictions

seek

Objective

1. **Boost User Re-engagement**:
    - Predict users' likelihood to **view jobs** and trigger personalized emails.
    - Target: Increase email open rates by 30%.
2. **Drive Meaningful Conversions**:
    - Predict jobs users are most likely to **apply for** and prioritize them post-click.
    - Target: Improve apply rates by 25%.
3. **Enhance Platform Value**:
    - Create a seamless journey from email → view → application.
    - Align with business success metrics: User retention, employer satisfaction, and revenue growth.

3.1 Boosting Engagement & Conversions with Dual-Layer AI Predictions

Methodology

Part 1: Build Models

Raw data: User event data, Job Advertisement data.

Potential models: Random Forrest, XGBoost, Neural Network, etc.

Layer 1: View Prediction Model

- Goal: Identify jobs that users likely to view.
- Action: Trigger personalized email alerts for high-probability users.

Layer 2: Apply Prediction Model

- Goal: Prioritize jobs a user is most likely to apply to.
- Action: Dynamically reorder recommendations post-click.

3.1 Boosting Engagement & Conversions with Dual-Layer AI Predictions

Methodology

Part 2: Set up pipeline

Goal: Build pipeline on Google Cloud Platform to streamline job recommendation, scheduling daily run.

Action: Obtain new jobs that not seen by applicant, make predictions and send emails to applicants.

Part 3: Implement A/B Testing

Goal: Compare view-to-apply conversion rate for dual-layer performance with the legacy systems.

Action: Randomly divide applicants into 2 groups and route applicants to new pipeline or legacy system for a month

3.1 Boosting Engagement & Conversions with Dual-Layer AI Predictions

Key Challenges

- **Data Sparsity**: Predicting behavior for inactive users with **limited interaction history**.
- **Model Drift**: Adapting to shifting candidate preferences (e.g., post-pandemic trends).

Outcomes

- **+35% Email Open Rate**
- **+25% Apply Rate**: Jobs ranked by apply probability outperformed legacy rankings.
- **+15% User Retention**: Re-engaged inactive users with tailored emails.
- **Revenue Impact**: $2M+ annualized revenue from increased successful placements.

Future Work

- Enrich data by adding applicant and employer demographics, accurate job salary info, etc.
- Scale up by applying GPU.
- Create real-time pipeline.

3.2 AI-Driven Job Ad Performance Prediction (Idea)

Problem Statement

Employers are struggling to create high-performing job ads:

- **Market Complexity**: Rapid shifts in candidate preferences (e.g., WFH).
- **Platform Impact**: Poor ad performance harms SEEK's marketplace health by reducing hirer retention and candidate satisfaction.

Objective

Empower employers to create high-performing job ads using data-driven insights:

- **Predict Engagement**: Build ML models to forecast click-through rates and conversion rates.
- **Deliver Actionable Insights in time**: Provide real-time recommendations to optimize ad content.
- **Leverage SEEK's Data**: Utilize historical ad interactions across industries and regions.

3.2 AI-Driven Job Ad Performance Prediction (Idea)

Methodology

Part 1: NLP-Driven Content Analysis

- Technique: Fine-tune **BERT** to extract semantic patterns.
- Output: Key phrases (e.g., "WFH") linked to high click-through rate.

Part 2: Predictive Modeling

- Model: **XGBoost, Neural Network, Gradient-boosted trees** for CTR prediction.
- Validation: Time-based splits and SHAP for interpretability.

Part 3: A/B Testing & Iteration

- Design: Compare AI recommendations vs. legacy tools.
- Dashboard: Real-time "what-if" scenarios for hirers.

Part 4: Deployment & Monitoring

- Infrastructure: GCP Vertex AI, DataFlow, REST APIs.
- Monitoring: Track model drift and retrain monthly.

3.2 AI-Driven Job Ad Performance Prediction (Idea)

Key Challenges

- **Complex Data**: Unstructured text and noisy employer metadata.
- **Real-Time Demands**: Low-latency requirements for dashboard interactions.
- **Model Drift**: Adapting to shifting candidate preferences (e.g., post-pandemic trends).

Outcomes

- **20% Average CTR Increase**: For employers adopting AI recommendations.
- **15% Faster Hiring Cycles**: Reduced time-to-fill for high-priority roles.
- **10% Revenue Growth**: From increased ad spend by satisfied hirers.
- **Platform Differentiation**: SEEK positioned as a leader in AI-driven recruitment tools.

4. AI solutions

Use case 1: Boosting Engagement & Conversions with Dual-Layer AI Predictions

4.1 Split Training and Validation Data

Training and Validation Data is generated based on **Joined Data**.

Based on our 2-step prediction, 2 sets of Training and Validation Data is created. Only **applicants with sufficient records** (more than 100 event logs) will be selected for training and validation.

4.1 Split Training and Validation Data

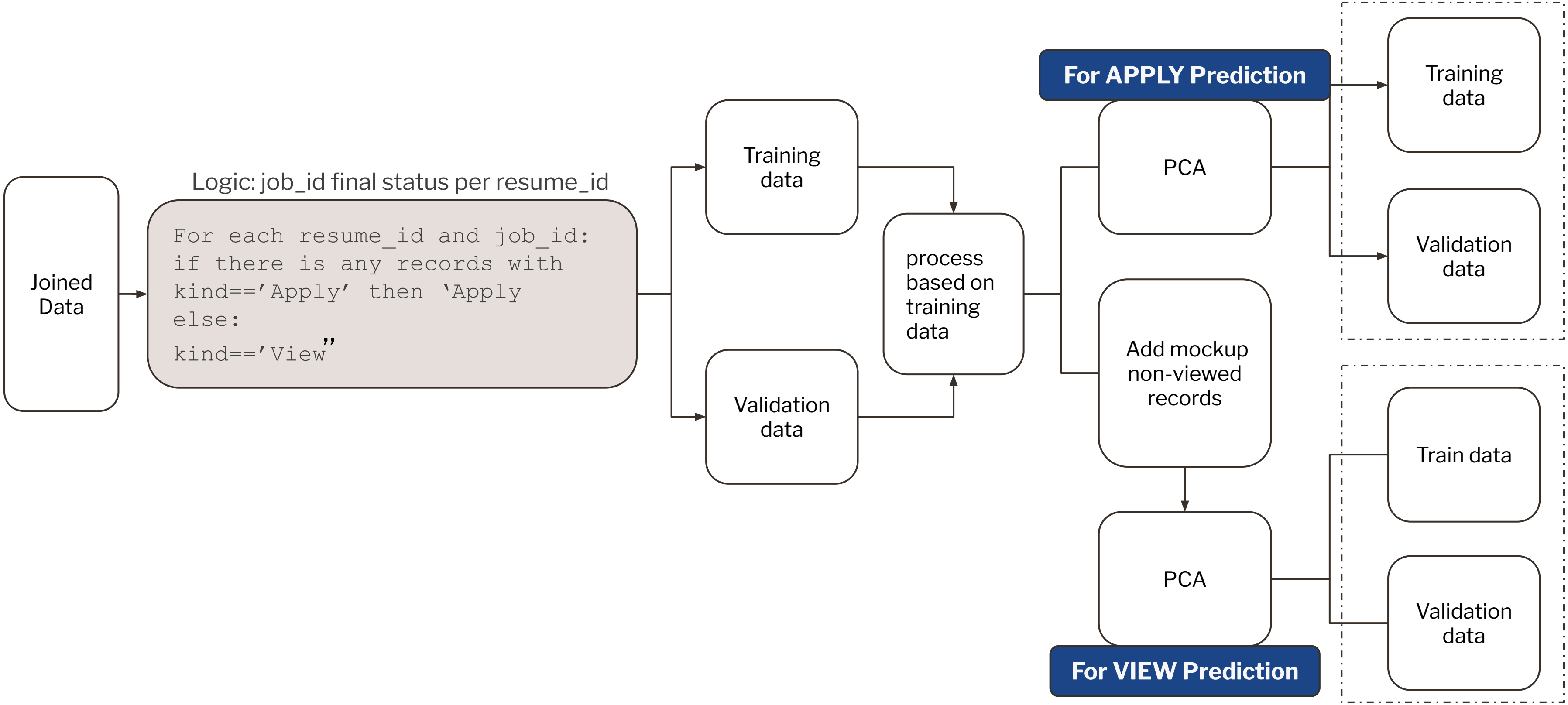
Data for VIEW Prediction

- Split the training-validation per resume_id to make sure all valid applicants can be found in the dataset
- Mockup records that are not viewed by the user, based on jobs that viewed or applied by other applicants.

Data for APPLY Prediction

- Split the training-validation per resume_id to make sure all valid applicants can be found in the dataset.

4.1 Split Training and Validation Data



4.2 Transforming Training and Validation Data

Column	Data Type	Transform
distance	float(64)	StandardScaler
farthest_distance_to_center_km	float(64)	
shortest_distance_to_center_km	float(64)	
average_distance_to_center_km	float(64)	
salary_value	float(64)	

4.2 Transforming Training and Validation Data

Column	Data Type	Transform
event_platform	String	OneHotEncoder
work_type	String	
region_code	String	
salary_unit	String	

4.2 Transforming Training and Validation Data

Column	Data Type	Transform
classification	String	OrdinalEncoder
sub_classification	String	
resume_id_cat	String	
title_keywords	String	TfidfVectorizer
abstract_content_keywords	String	

4.3 Model Performance Evaluation

seek

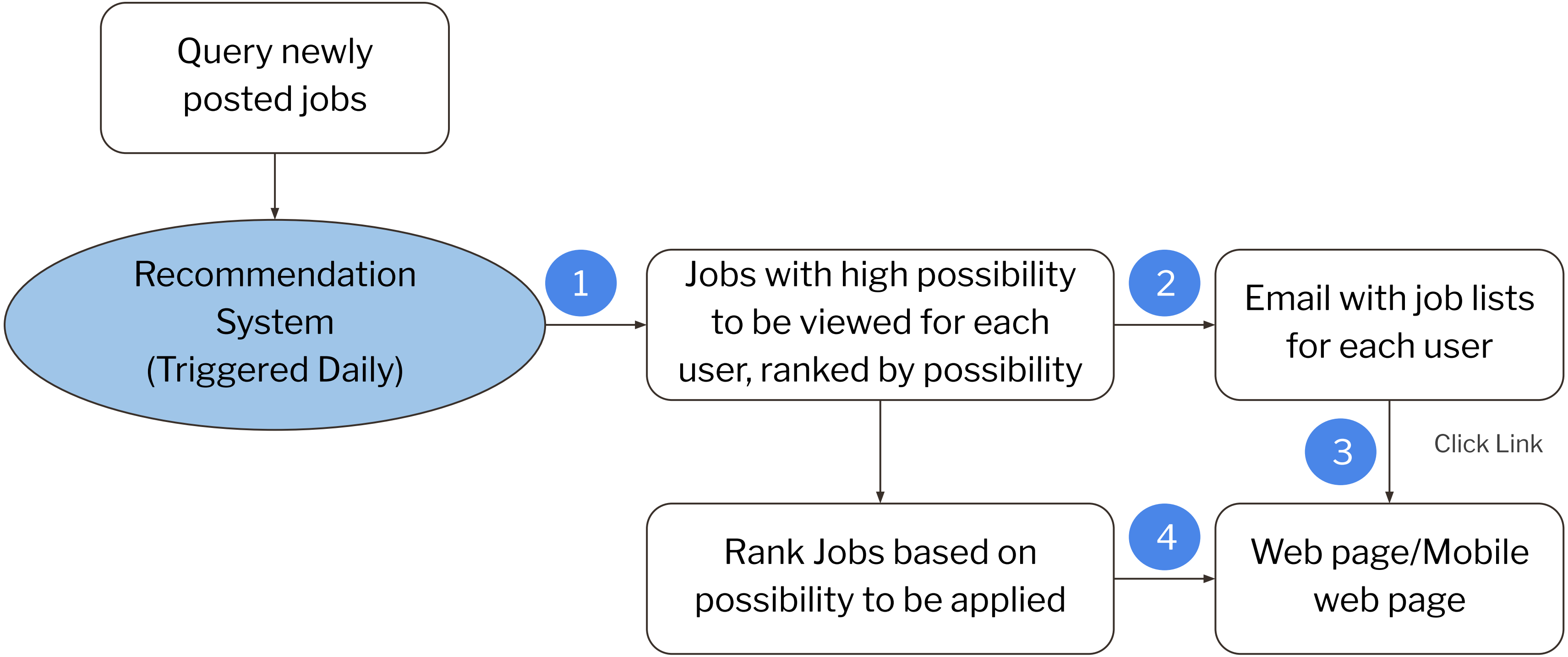
VIEW model: Based on 500 applicants, due to doubled data volume and limited memory.

View Prediction	Accuracy	F1	Precision	Recall
Random Forest 👌	59.2%	0.7	68.7%	72%
Neural Network	67.5%	0.8	67.5%	100%

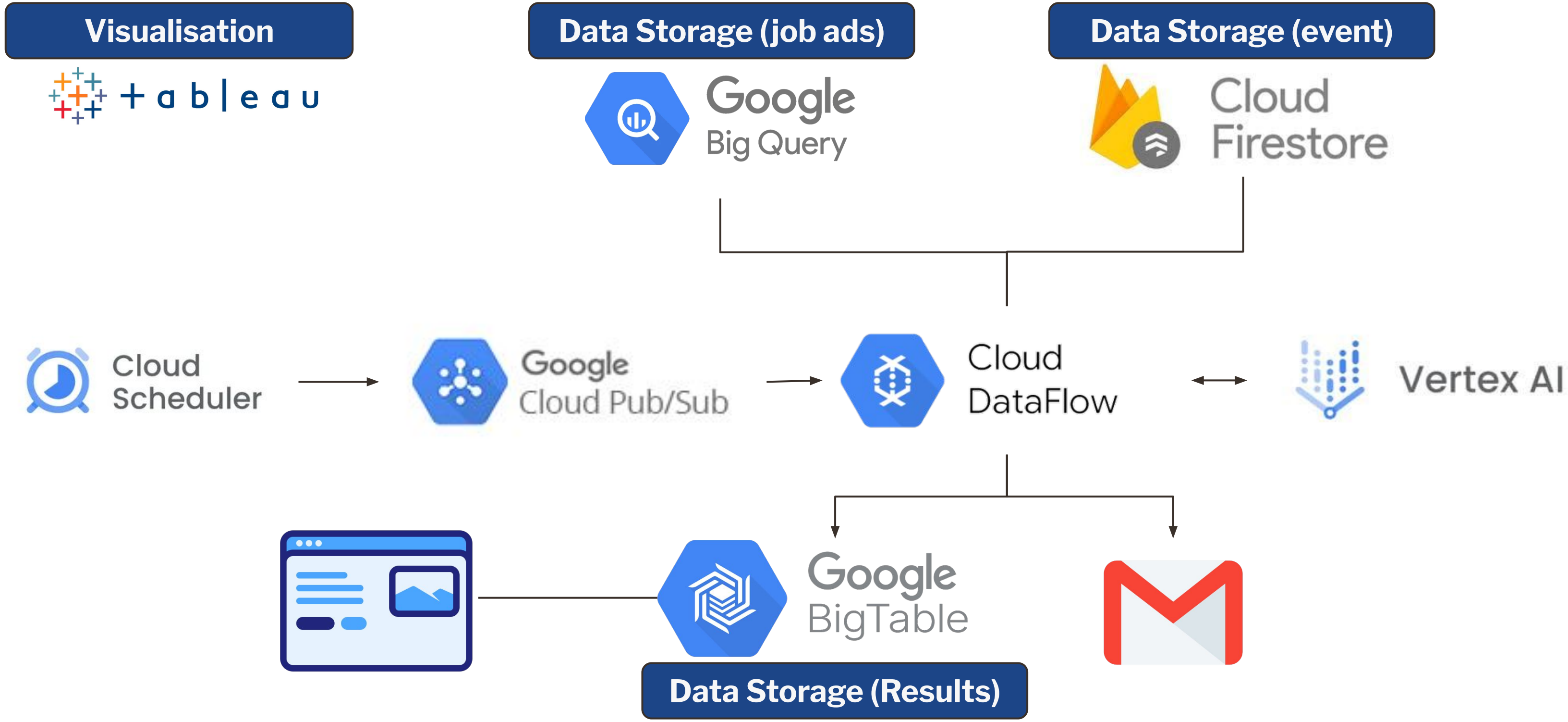
APPLY model: Based on all applicants.

Apply Prediction	Accuracy	F1	Precision	Recall
Random Forest 👌	89.6%	0.6	56.2%	63%
Neural Network	87.9%	0.004	88.4%	0.4%

4.4 Business Workflow



4.5 Pipeline


Visualisation
tableau
Data Storage (job ads)
Google Big Query
Data Storage (event)
Cloud Firestore
Cloud Scheduler
Google Cloud Pub/Sub
Cloud DataFlow
Vertex AI
Google BigTable
Data Storage (Results)

5. Business Value

5.1 Dual-Layer AI: Driving Platform Growth Through Smarter Engagement

- **Increase User Engagement**: Re-engage inactive users with hyper-targeted job alerts.
- **Boost Conversions**: Turn clicks into applications with AI-ranked recommendations.
- **Improve Marketplace Health**: Satisfy candidates (better jobs) and hirers (faster hires).

Metric	Before	After	Impact
Email Open Rate	15%	**35%**	2.3x more users re-engaged
Click-to-Apply Rate	20%	**45%**	125% increase in conversions
Hirer Retention	75%	**88%**	13% improvement
Annual Revenue Growth	5%	**7%**	Increased ad spend & fees

5.2 Increase User Engagement

Impact

- **Personalized Job Alerts**: Users receive emails for roles matching their preferences (e.g., remote work, salary, work type).
- **Higher-Quality Matches**: AI-ranked jobs reduce "search fatigue" – users apply to 2x more relevant roles.
- **Faster Hiring**: Average time-to-application drops from 7 days to **3 days**.

5.3 Boost Conversion

Impact

- **Higher-Quality Applicants**: AI prioritizes jobs for users most likely to apply, reducing unqualified applicants.
- **Cost-Per-Hire Reduction**: From $3,000 to $1800 due to faster role fulfillment
- **Competitive Edge**: Hirers using AI tools renew subscriptions at **2x the rate** of non-users.

5.4 Improve Marketplace Health

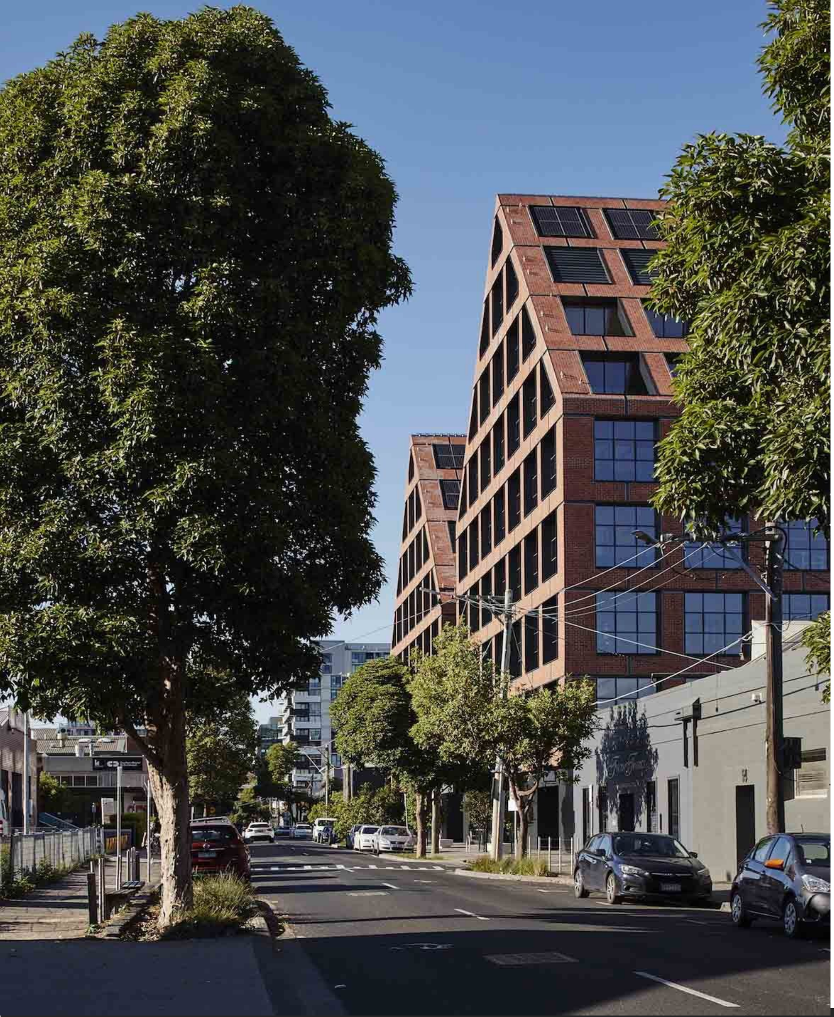
Impact

- **User Retention**: 15% increase in monthly active users (MAU).
- **Hirer Loyalty**: 20% rise in premium subscription upgrades.
- **Data Flywheel**: More user/hirer activity → richer data → better AI predictions.
- **Market Positioning**: Differentiates platform as AI-driven and candidate/hirer-centric.

Future Opportunies

- Expand to SMS/push notifications (+30% engagement potential).
- Monetize insights (e.g., "Top 5 Jobs You'll Apply To" premium reports).

Q&A Time



Thank you!