



California State University, Chico

**MATH 485 - Advanced Topics in
Data Science**

Final Report

Professor:
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1. Title

Job Market Analysis Using Clustering, Salary Prediction, and Skill Network Analysis.

2. Team Member Names

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3. Overall Context and Relevant Work

In today's dynamic job market, understanding trends, skill demands, and salary expectations is critical. Our project addresses these issues by analyzing job postings to derive actionable insights using clustering, salary prediction, and skill network analysis.

This project utilizes advanced data science techniques to enhance decision-making for job seekers and recruiters. By extracting insights from job listings, we can identify trends, predict salaries, and map skill requirements, facilitating strategic career and hiring decisions.

4. High-Level Framework

Our solution uniquely integrates:

- **Clustering:** Categorizes job postings based on roles and required skills.
- **Salary Prediction:** Uses regression models to estimate salaries from job descriptions.
- **Skill Network Analysis:** Creates a visual representation of co-occurring skills.
- **Interactive Dashboard:** Presents the findings through user-friendly visualization tools.

5. Detailed Aspects of the Solution

5.1 Implementation Summary

- **Data Collection and Preprocessing:**
 - Utilized free job listing Adzuna API to collect job postings.
 - Processed data to handle missing values and duplicates.
- **Job Clustering:**
 - Applied clustering algorithms like K-means and Hierarchical clustering.
 - Identified optimal clustering features to enhance cluster quality.
- **Salary Prediction:**
 - Developed regression models considering job title, skills, and location.
 - Evaluated and optimized models for accuracy and robustness.
- **Skill Network Analysis:**
 - Built network graphs to visualize skill interrelationships.

5.2 Focus on Your Solution

The uniqueness of our solution lies in its integrative approach, combining robust data preprocessing, sophisticated clustering methods, predictive modeling, and visual skill relationship mapping. Our interactive dashboard further distinguishes our work by allowing users to dynamically explore insights.

5.3 Important Code Snippets

```
def cluster_jobs(self, n_clusters=5):
    """
    Cluster jobs based on skills and features
    """
    if self.df.empty:
        return self.df

    skill_matrix = self.create_skill_matrix()
    if skill_matrix.empty:
        self.df['cluster'] = 0
        return self.df

    # Add numerical features
    features = pd.concat([
        skill_matrix,
        self.df[['skill_count']]
    ], axis=1)

    # Scale features
    scaler = StandardScaler()
    scaled_features = scaler.fit_transform(features)

    # Perform clustering
    kmeans = KMeans(n_clusters=min(n_clusters, len(self.df)), random_state=42)
    self.df['cluster'] = kmeans.fit_predict(scaled_features)
```

```
def get_top_skills(self, n=10):
    """
    Get the most common skills across all job postings
    """
    skill_matrix = self.create_skill_matrix()
    if skill_matrix.empty:
        return pd.Series()
    skill_counts = skill_matrix.sum().sort_values(ascending=False)
    return skill_counts.head(n)
```

```

def analyze_salary_by_skill(self):
    """
    Analyze average salary for each skill
    """
    if self.df.empty or 'avg_salary' not in self.df.columns:
        return pd.Series()

    skill_matrix = self.create_skill_matrix()
    if skill_matrix.empty:
        return pd.Series()

    # Calculate average salary for each skill
    salary_by_skill = {}
    for skill in skill_matrix.columns:
        skill_jobs = self.df[skill_matrix[skill] == 1]
        if not skill_jobs.empty:
            avg_salary = skill_jobs['avg_salary'].mean()
            if not pd.isna(avg_salary):
                salary_by_skill[skill] = avg_salary

    return pd.Series(salary_by_skill).sort_values(ascending=False)

```

```

def get_top_companies(self, n=10):
    """
    Get the companies with the most job postings
    """
    if self.df.empty:
        return pd.Series()
    return self.df['company'].value_counts().head(n)

def get_top_locations(self, n=10):
    """
    Get the locations with the most job postings
    """
    if self.df.empty:
        return pd.Series()
    return self.df['location'].value_counts().head(n)

def get_job_types_distribution(self):
    """
    Get the distribution of job types
    """
    if self.df.empty:
        return pd.Series()
    return self.df['type'].value_counts()

```

6. Test Results and Analysis

6.1 Comparison of Solutions

- **Early Models:** Initially faced challenges due to incomplete feature sets and basic preprocessing.
- **Improved Approach:** Enhanced data processing and feature selection significantly improved model accuracy and clustering effectiveness.

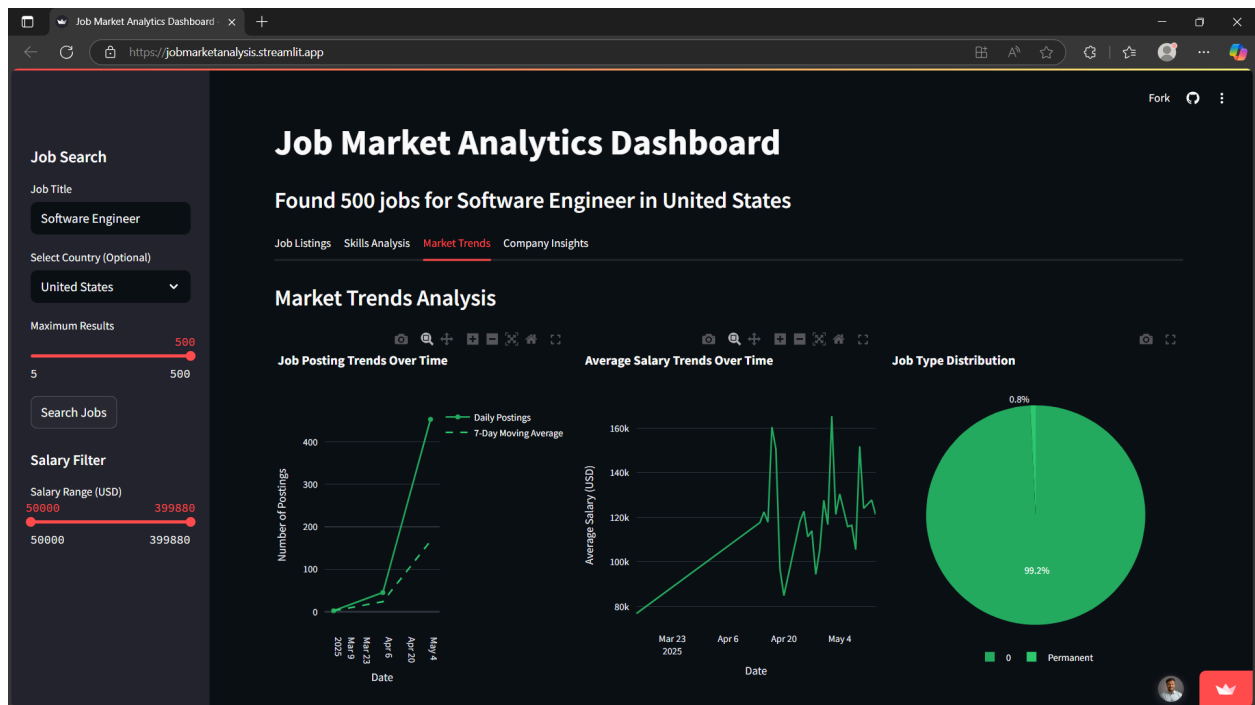
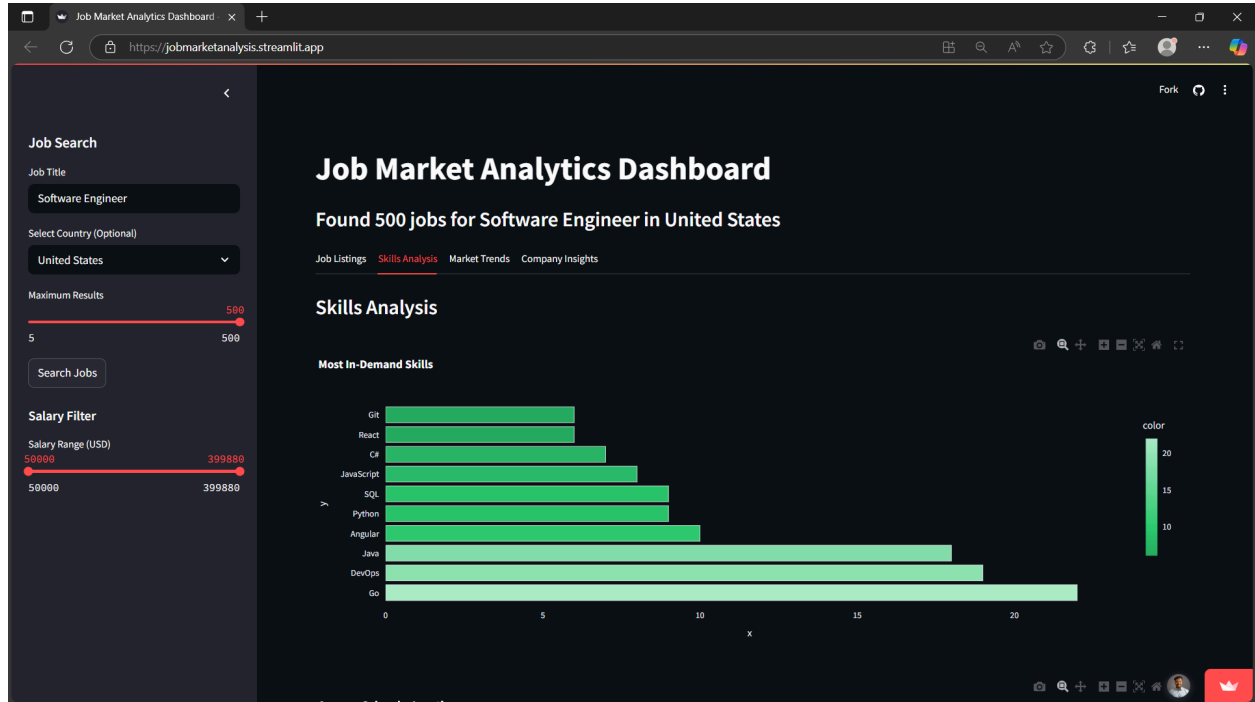
6.2 Comparison with Other Solutions

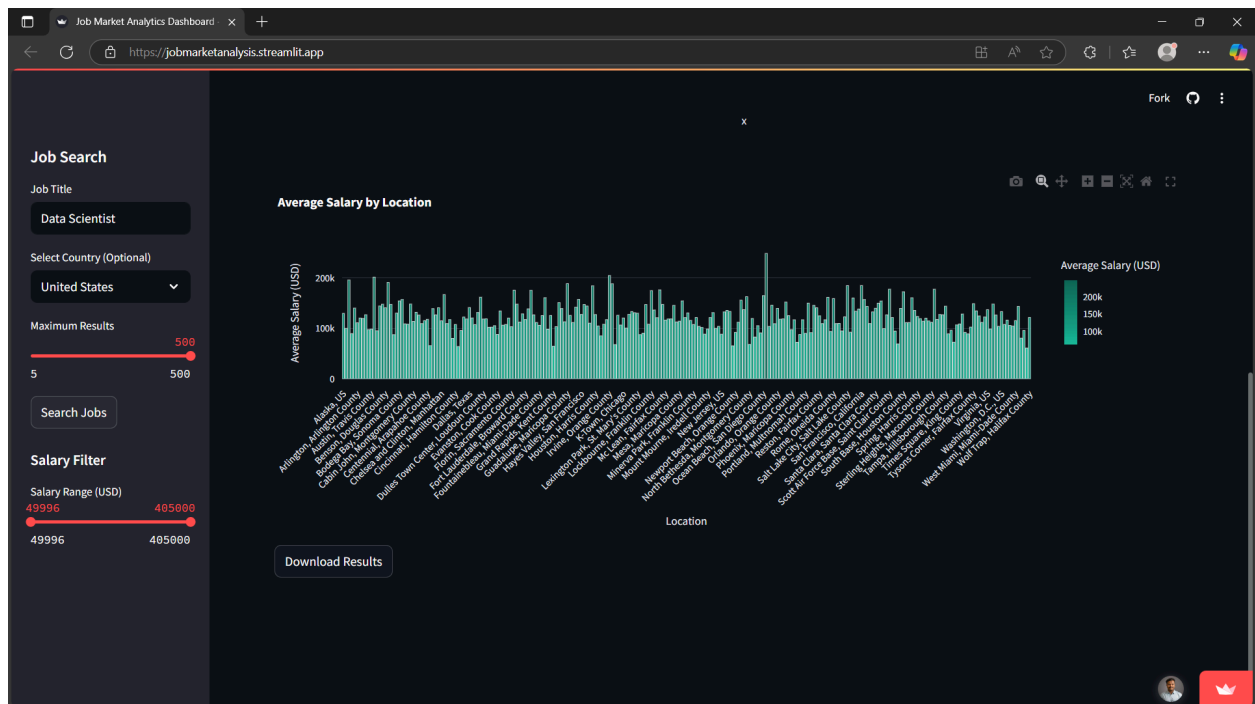
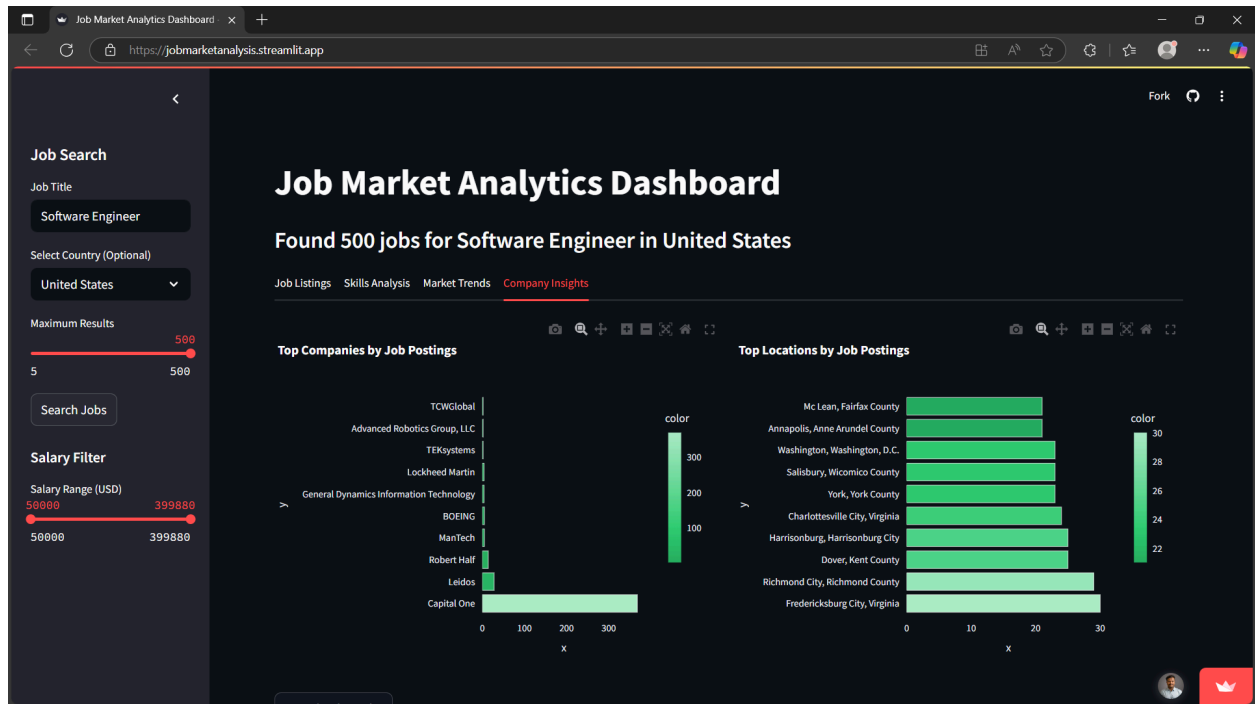
- Our combined methodology of clustering, regression, and network visualization offered deeper insights compared to singular analytical approaches.
- The integration of multiple features enhanced predictive accuracy over simpler models.

6.3 What Worked vs What Didn't

- **Effective Approaches:**
 - Comprehensive preprocessing and advanced feature engineering.
 - Efficient integration of analytical techniques.
- **Areas of Improvement:**
 - Data quality initially affected analysis outcomes.
 - Initial complexities in network graph visualization required additional optimization.

7. Dashboard





Dashboard Link:- <https://jobmarketanalysis.streamlit.app/>

8. Conclusion

Our integrated analytical approach provides valuable insights into the job market, significantly benefiting stakeholders through enhanced decision-making support.

9. Future Work

- Expansion of dataset scope and geographical diversity.
- Further refinement of dashboard interactivity and user experience.
- Exploration of advanced analytical models to enhance predictive capabilities.