CareerVillage Questions Matching Recommendation System

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Context & Problem Statement

- CareerVillage.org, a non-profit for career guidance, aims to boost impact through a data-driven recommendation system.
- The system connects students' questions with suitable volunteers, enhancing connections between aspiring individuals and experienced professionals.
- Leveraging data science, the project optimizes engagement, ensuring students receive valuable advice, empowering underserved youth with career role models.
- The CareerVillage Question Recommendation Model efficiently matches students' questions with professionals, outlined in this report covering methodology, data exploration, model development, and key findings.

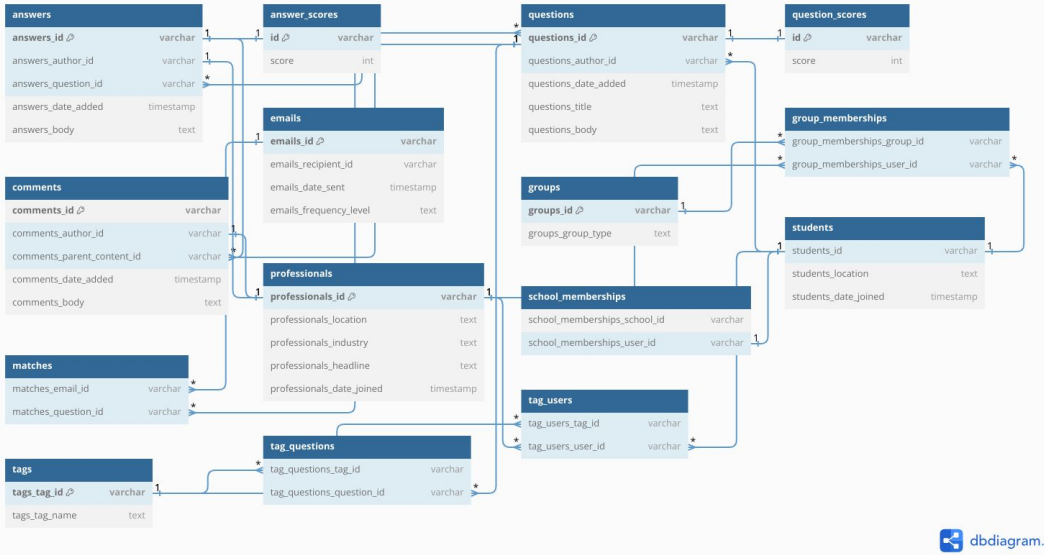
Methodology

Content-based Approach

- Privacy is a top priority; no personal or usage data is stored or used for training in the recommendation system.
- The project opts for a content-based approach to address privacy concerns.
- Two recommendation models were created, building professional profiles from past answered questions and tags.
- These models were evaluated based on recommendation success rates, comparing favorably to existing approaches.

Data

Source: Kaggle-provided data from CareerVillage.



Data

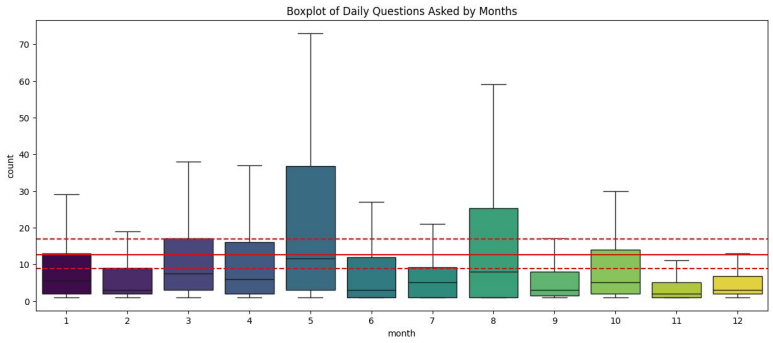
Key Tables:

- Questions: 23,931 records
- Professionals: 28,152 records
- Answers: 23,110 records
- Emails:
- Matches:

Exploratory Data Analysis

Key findings:

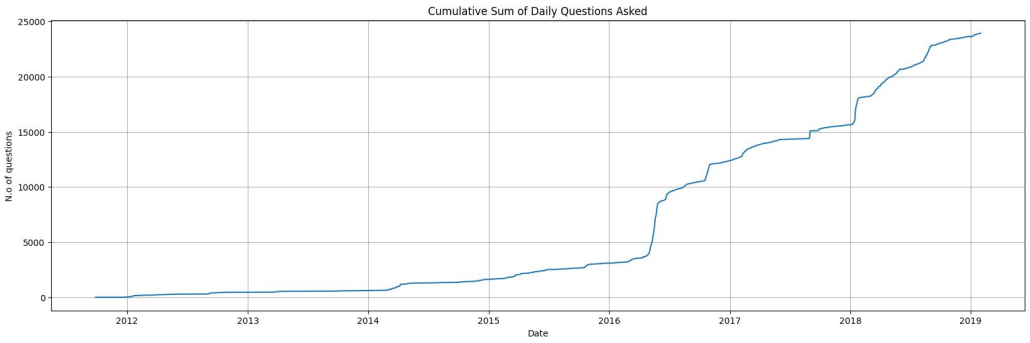
- Peak in daily questions during graduation months.



Exploratory Data Analysis

Key findings:

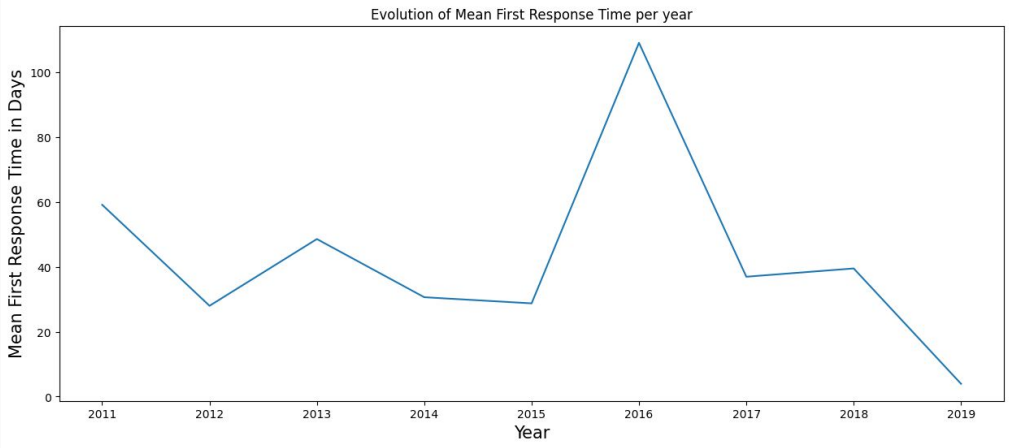
- Significant increase in questions since 2016



Exploratory Data Analysis

Key findings:

- Average response time for questions is 65 days.



Data Cleaning & Preprocessing

- Most time-consuming step.
- Multiple tables required merging and examination.
- Goal: Understand table relations and create data for modeling.

Data Cleaning & Preprocessing

Train/Test Split:

- Unconventional split based on midpoint of answers table by date.
- Train set: Professional IDs, combined content of past questions, list of tags for each professional.

Data Cleaning & Preprocessing

Professionals and Questions Profiles:

- Merged questions and answers for profiles in the train set.
- Created a question_tag_list table with tags associated with each question.
- Merged professionals with tag_users to create tags feature.
- Combined data frames for professional profiles: professional IDs, tags, content of past answered questions

Data Cleaning & Preprocessing

Test Set Profiles and Text Cleaning:

- Applied the same merging technique for profiles in the test set.
- Text cleaning function: Removed special characters, stopwords, digits; lemmatized and converted text to lowercase.

Data Cleaning & Preprocessing

Handling Missing Values:

- Two approaches considered for missing tags.
- Chose to impute missing tag values with "no_tag" for simplicity.
- Second approach (auto-tag-generated function) considered for future improvement.

Modeling - Question-Content Based

TF-IDF Vectorization

- Transformed textual content of train set questions into numerical vectors using TF-IDF.
- Assigned weights to words based on importance, creating a numerical representation.

Modeling - Question-Content Based

Model Training:

- Trained the model using TF-IDF vectors and professional response data.
- System learned relationships between question content features and professional preferences.

Modeling - Question-Content Based

Recommendation Generation:

- Assessed content similarity using cosine similarity.
- Identified questions with similar attributes based on historical preferences.
- Generated recommendations of 10 professionals for each question.

Modeling - Tags-based

- Built a similar model using the same techniques as the content-based model.
- Employed tags of professionals and questions to calculate cosine similarity.

Model Evaluation - Evaluation Metrics

- Establishing a nuanced matching score for professionals and questions.
- Criteria for success include Answer Rating, Response Time, and Response Rate.
- Emphasizes the inadequacy of the current answer rating system during EDA.
- Advocates for a more sophisticated rating system for robust evaluation.

Model Evaluation - Response Rate and Time Metrics

- Response Rate: Ratio of responses to total assigned questions, gauges engagement.
- Response Time: Duration to respond plays a crucial role in efficiency assessment.

Model Evaluation - Evaluation Process

- Initial focus on utilizing Response Rate as a predominant metric.
- Determining original response rates of questions in the test set.
- Merging emails and matches to identify assigned questions.
- Calculating the average response rate of the original matching system.

Model Evaluation - Model-Specific Response Rates

- Determining response rates with question-content-based recommendation.
- Model recommends questions to 10 relevant profession
- Calculating the average response rate for the content-based recommendation mod

Model Evaluation - Model-Specific Response Rates

- Determining response rates with tags-based recommendation.
- Using the same method as the content-based model.
- Calculating the average response rate for the tags-based recommendation model.

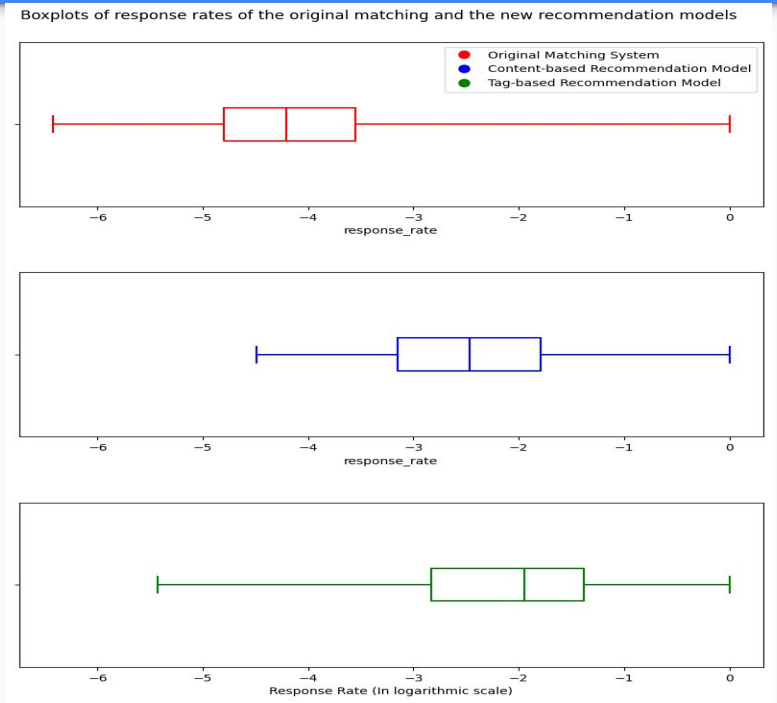
Model Evaluation - Comparison of Average Response Rates

- Involves creating boxplots for original system and two recommendation models.
- Comparison includes question content-based recommendation and tags-based recommendation.
- Rates transformed to logarithmic scale for clarity.

Model Evaluation - Comparison of Average Response Rates

Average response rate

- **Original matching system: 0.38%**
- **Question content-based recommendation model: 0.42%**
- **Tags-based recommendation model: 0.60%**



Future Steps

- Integrate response time into the success metric.
- Consider professional activeness as a feature.
- Include professionals' previous responses in training.
- Implement dynamic tagging for evolving expertise.
- Establish a user feedback loop and improve user rating mechanism.
- Explore advanced collaborative filtering techniques.

Project Impact

Significantly enhances the CareerVillage platform, empowering students with career guidance and fostering meaningful connections.

Recommendations and insights provide a solid foundation for future enhancements, ensuring a more personalized and impactful user experience on CareerVillage.org.

Thanks!

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