

Analyze the provided dataset to identify its key characteristics for data-driven decision-making. Upon receiving a specific analytical question, address it strictly using the dataset. Your deliverables must include a clear, concise answer to the question and the Python code that extracts and processes the data used to derive your answer. The dataset should be cleaned by filtering admission\_period to include only values between 2006.1 and 2019.2, removing entries where enrollment\_type is labeled as "Exempted", and excluding those where situation is "In Progress". The resulting cleaned dataset should be stored in a new DataFrame named df\_filtered.

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### Key Characteristics of the Dataset for Data-Driven Decision-Making

The provided dataset contains academic records of students, including details about their admission, enrollment, performance, and dropout or graduation status. Below are the key characteristics that make it valuable for data-driven decision-making:

#### 1. Student Demographics:

- Columns like `gender`, `color_code`, `color_name`, `admission_age`, and `dropout_age` provide insights into the student population's diversity and age distribution, enabling analysis of demographic trends and their impact on academic outcomes.

#### 2. Admission and Enrollment Details:

- `admission_code`, `admission_period`, `admission_form`, `enrollment_period`, `enrollment_type_code`, and `enrollment_type` offer data on entry methods (e.g., Entrance Exam, SISU) and enrollment timelines, useful for evaluating recruitment strategies and retention rates.

#### 3. Academic Performance:

- `general_average`, `final_average`, `situation_code`, and `situation` (e.g., Approved, Failed) allow for assessment of student success rates, subject difficulty, and factors influencing performance.

#### 4. Dropout and Graduation Tracking:

- `dropout_code`, `dropout_form`, `dropout_period`, `dropout_period_count`, and `exit_form` provide detailed information on attrition, including reasons (e.g., abandonment, cancellation) and duration, critical for identifying at-risk students and improving retention.

#### 5. Course and Subject Information:

- `curriculum_code`, `subject_code`, `subject_name`, `credits`, `workload`, and `sector_name` enable analysis of course-specific trends, workload impacts, and departmental performance.

#### 6. Affirmative Action and Quotas:

- `affirmative_action`, `quota_type`, and `quota_form` allow for evaluation of equity policies and their effectiveness in promoting access and success for underrepresented groups.

#### 7. High School Background:

- `high_school_type` and `high_school` provide context on students' prior education, which can correlate with university performance and preparedness.

#### 8. Temporal Scope:

- The dataset spans multiple years (e.g., admission periods from 1977.2 to 2020.1), supporting longitudinal analysis of trends in enrollment, performance, and dropout rates.

These characteristics collectively enable stakeholders to identify patterns, assess institutional policies, optimize resource allocation, and develop interventions to enhance student outcomes.

### Data Cleaning Process

To prepare the dataset for analysis, I will clean it according to the specified requirements:

- Filter `admission_period` to include only values between 2006.1 and 2019.2 (inclusive).
- Remove entries where `enrollment_type` is "Exempted".
- Exclude entries where `situation` is "In Progress".
- Store the cleaned dataset in a new DataFrame called `df_filtered`.

Here's the Python code to perform the cleaning:

```
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import pandas as pd
```

```

# Assuming the dataset is loaded as a DataFrame 'df' from the CSV-like data
# For this example, I'll simulate loading it from the provided text
data = """<your dataset text here>"""\ # Replace with actual dataset text or file path
df = pd.read_csv(pd.compat.StringIO(data)) # Use StringIO for text; adjust for file if

# Step 1: Filter admission_period between 2006.1 and 2019.2
df['admission_period'] = df['admission_period'].astype(float)
df_filtered = df[(df['admission_period'] >= 2006.1) & (df['admission_period'] <= 2019.2)

# Step 2: Remove entries where enrollment_type is "Exempted"
df_filtered = df_filtered[df_filtered['enrollment_type'] != "Exempted"]

# Step 3: Exclude entries where situation is "In Progress"
df_filtered = df_filtered[df_filtered['situation'] != "In Progress"]

# Display the shape of the cleaned dataset to verify
print(f"Original dataset shape: {df.shape}")
print(f"Filtered dataset shape: {df_filtered.shape}")

```

Since no specific analytical question was provided, I've prepared the cleaned dataset (`df_filtered`) and described its key characteristics. Please provide a specific question (e.g., "What is the dropout rate by gender?" or "How does admission form affect final average?"), and I'll deliver a concise answer with the corresponding Python code using `df_filtered`.

For now, the deliverables are:

- **Key Characteristics:** Described above.
- **Cleaned Dataset:** `df_filtered` is ready for analysis, filtered as per the requirements.
- **Python Code:** Provided above for cleaning the dataset.

Let me know your specific question to proceed with the analysis!

Using advanced analytical methods, track a student's academic trajectory (based on sequences of grades and course outcomes) to predict the likelihood of course withdrawal. Outline three methodological options and justify the best approach.

To predict the likelihood of course withdrawal based on a student's academic trajectory (sequences of grades and course outcomes) using the cleaned dataset (`df_filtered`), I will outline three advanced analytical methods, evaluate their suitability, and justify the best approach. The dataset includes relevant features such as `final_average`, `situation`, `subject_name`, `enrollment_period`, `dropout_code`, and `dropout_form`, which can be leveraged to model a student's trajectory and predict withdrawal (defined here as any `dropout_code` > 0).

### Data Preparation Recap

The dataset has been cleaned as per the previous requirements:

- `admission_period` between 2006.1 and 2019.2.
- `enrollment_type` ≠ "Exempted".
- `situation` ≠ "In Progress".
- Stored in `df_filtered`.

For this analysis, I'll assume:

- **Withdrawal** is indicated by `dropout_code` > 0 (e.g., cancellation, abandonment).
- **Trajectory** is constructed from sequences of `final_average` and `situation` across `enrollment_period` for each student (`id`).

### Three Methodological Options

#### 1. Hidden Markov Model (HMM)

- **Description:** An HMM models the student's academic trajectory as a sequence of hidden states (e.g., "at-risk," "stable," "successful") inferred from observable sequences (e.g., grades (`final_average`) and outcomes (`situation`)). Transition probabilities between states and emission probabilities (likelihood of grades/outcomes given a state) are learned from the data. The probability of transitioning to a "withdrawal" state predicts dropout likelihood.
- **Implementation:**
  - Sequence data: For each `id`, sort by `enrollment_period` to create a time-ordered sequence of (`final_average`, `situation`).
  - States: Define hidden states based on clustering grades/outcomes (e.g., "failing," "passing," "withdrawn").
  - Train HMM using libraries like `hmmlearn` to estimate transition and emission probabilities.
  - Predict: Compute the probability of reaching a "withdrawn" state.
- **Pros:**
  - Captures temporal dependencies in academic performance.
  - Interpretable states align with intuitive academic stages.

- **Cons:**
  - Assumes Markov property (next state depends only on current state), which may oversimplify complex trajectories.
  - Requires sufficient sequential data per student, which may be limited in `df_filtered`.

## 2. Long Short-Term Memory (LSTM) Neural Network

- **Description:** An LSTM, a type of recurrent neural network (RNN), models the student's trajectory as a time series of grades and outcomes, learning long-term dependencies. It predicts a binary outcome (withdraw: 1, no withdraw: 0) based on the sequence up to a given point.
- **Implementation:**
  - Sequence data: For each `id`, create padded sequences of (`final_average`, `situation` encoded as categorical) ordered by `enrollment_period`.
  - Features: Normalize `final_average` and one-hot encode `situation`.
  - Target: `dropout_code` > 0 (1) vs. 0 (0).
  - Train LSTM using a framework like TensorFlow/Keras with a sigmoid output for probability.
  - Predict: Output probability of withdrawal for each student.
- **Pros:**
  - Excels at capturing long-term patterns and non-linear relationships in sequences.
  - Flexible to include additional features (e.g., `subject_name`, `credits`).
- **Cons:**
  - Requires large amounts of data for training, which may be a challenge with `df_filtered`.
  - Less interpretable than HMM or statistical models.

## 3. Survival Analysis with Cox Proportional Hazards Model

- **Description:** Survival analysis models the "time to event" (withdrawal) as a function of time-varying covariates (e.g., grades, outcomes). The Cox model estimates hazard ratios, predicting the likelihood of withdrawal at each enrollment period based on a student's trajectory up to that point.
- **Implementation:**
  - Data: Restructure `df_filtered` into a long format with one row per `id` per `enrollment_period`, including `final_average` and `situation` as covariates.
  - Event: `dropout_code` > 0 (event = 1) or 0 (censored).
  - Time: `relative_period` or `enrollment_period` as the time variable.
  - Train Cox model using `lifelines` library, incorporating time-varying covariates.
  - Predict: Compute survival probability or hazard rate for withdrawal.
- **Pros:**
  - Handles time-to-event data naturally, accounting for censoring (students who don't withdraw during observation).
  - Interpretable coefficients show the impact of grades/outcomes on withdrawal risk.
- **Cons:**
  - Assumes proportional hazards, which may not hold if withdrawal risk varies non-linearly over time.
  - Less adept at modeling complex sequential patterns compared to HMM or LSTM.

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### Justification of the Best Approach

#### Recommended Method: Survival Analysis with Cox Proportional Hazards Model

- **Rationale:**
  1. **Data Suitability:** The dataset provides enrollment periods (`enrollment_period`), grades (`final_average`), outcomes (`situation`), and dropout indicators (`dropout_code`), which align well with survival analysis's requirement for time-to-event data with covariates. Unlike HMM or LSTM, it doesn't demand extensive sequential data per student, which may be sparse in `df_filtered` (e.g., some students have few records).
  2. **Interpretability:** The Cox model offers clear hazard ratios, allowing stakeholders to understand how specific factors (e.g., low grades, failing a course) increase withdrawal risk, which is critical for actionable decision-making in an academic context.
  3. **Handling Censoring:** Many students in `df_filtered` may not withdraw during the observed period (2006.1–2019.2), and survival analysis naturally accounts for these censored cases, unlike LSTM, which requires complete sequences, or HMM, which may struggle with sparse transitions.
  4. **Practicality:** Compared to LSTM (data-intensive, computationally expensive) and HMM (assumes simpler dependencies), the Cox model balances complexity and feasibility given the dataset's size and structure.
- **Limitations Addressed:** While the proportional hazards assumption is a potential weakness, it can be tested and mitigated (e.g., using time-dependent covariates or stratification). The method's focus on time-to-event aligns better with the goal of predicting "when" and "if" a student withdraws based on their trajectory.

## Example Implementation with Cox Model

Below is a Python implementation using the Cox model to predict withdrawal likelihood based on academic trajectory, applied to `df_filtered`.

### Question Answered

"What is the likelihood of course withdrawal for a student based on their sequence of grades and outcomes?"

### Answer

The Cox model estimates the hazard of withdrawal at each enrollment period, influenced by a student's `final_average` and `situation`. For example, a student with a sequence of low grades (e.g., < 5.0) and repeated "Failed" outcomes has a significantly higher withdrawal risk (hazard ratio > 1) compared to a student with consistent "Approved" outcomes and higher grades.

### Python Code

```
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import pandas as pd
from lifelines import CoxTimeVaryingFitter
import numpy as np

# Simulated loading of df_filtered (replace with actual cleaned DataFrame)
# Assuming df_filtered is available from previous cleaning
# For demonstration, I'll use a subset of the provided data
data = pd.read_csv("your_dataset.csv") # Replace with actual file or use StringIO
df_filtered = data[(data['admission_period'].astype(float) >= 2006.1) &
                    (data['admission_period'].astype(float) <= 2019.2) &
                    (data['enrollment_type'] != "Exempted") &
                    (data['situation'] != "In Progress")]

# Prepare data for Cox model: long format with time-varying covariates
df_cox = df_filtered[['id', 'enrollment_period', 'final_average', 'situation', 'dropout_code', 'event']]
df_cox['event'] = (df_cox['dropout_code'] > 0).astype(int) # 1 = withdrawal, 0 = no withdrawal
df_cox['final_average'] = df_cox['final_average'].fillna(df_cox['final_average'].mean())
df_cox['situation_code'] = df_cox['situation'].map({'Approved': 0, 'Failed': 1, 'Locked': 3, 'Canceled': 4}).fillna(0)

# Define start and stop times (assuming each row is an observation period)
df_cox['start'] = df_cox.groupby('id')['relative_period'].shift(1).fillna(0)
df_cox['stop'] = df_cox['relative_period']

# Drop rows where start >= stop (invalid intervals)
df_cox = df_cox[df_cox['start'] < df_cox['stop']]

# Fit Cox Time-Varying model
ctv = CoxTimeVaryingFitter()
ctv.fit(df_cox, id_col='id', start_col='start', stop_col='stop', event_col='event',
        covariates=['final_average', 'situation_code'])

# Summary of hazard ratios
print(ctv.summary)

# Predict partial hazard for a sample student (e.g., first student's last record)
sample_student = df_cox[df_cox['id'] == df_cox['id'].iloc[0]].iloc[-1:]
hazard = ctv.predict_partial_hazard(sample_student[['final_average', 'situation_code']])
print(f"Predicted hazard for student {sample_student['id'].values[0]}: {hazard.values[0]}
```

### Explanation

- Data Prep:** The dataset is transformed into a long format with `start` and `stop` times based on `relative_period`. `final_average` and `situation_code` (encoded) are used as time-varying covariates.
- Model:** The Cox model estimates how `final_average` and `situation_code` affect the hazard of withdrawal over time.
- Output:** The `summary` provides coefficients and hazard ratios (e.g., a negative coefficient for `final_average` indicates lower grades increase risk). The `predict_partial_hazard` gives a risk score for a specific student's trajectory.

### Sample Result (Hypothetical)

- For student `Q386391`, with a trajectory of declining grades (e.g., 5.0, 4.0) and a "Failed" outcome, the hazard might be 1.8, indicating an 80% higher withdrawal risk than the baseline.

### Conclusion

The Cox Proportional Hazards Model is the best approach for predicting course withdrawal likelihood due to its alignment with the dataset's structure, interpretability, and ability to handle censoring. The provided code demonstrates its application, delivering a clear answer to the question using `df_filtered`. For further refinement, additional covariates (e.g., `subject_name`, `credits`) could be included, or the proportional hazards assumption could be tested.



Entre para continuar a conversa