Project Name: Credit Card Fraud Detection System – ML Pipeline with Production Focus

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Problem Statement:
Credit card fraud is a significant financial risk for banks. This project detects fraudulent transactions from millions of entries, helping reduce losses and maintain user trust.

Objectives:

- Build a machine learning model to classify genuine vs. fraudulent transactions.
- Address class imbalance for accurate predictions.
- Optimize model performance and reduce false alarms.
- Package the solution for seamless integration in production systems.

Input & Output:

- **Input:** Transactional data (amounts, time, customer features).
- **Output:** A fraud prediction label (fraudulent or not) for each transaction.

Technologies Used:

- Python for implementation.
- **Pandas & NumPy** for preprocessing and data manipulation.
- **XGBoost** for efficient and accurate classification modeling.
- **SMOTE** (Synthetic Minority Over-sampling Technique) to handle class imbalance.
- **PCA** (Principal Component Analysis) for dimensionality reduction.
- **KMeans Clustering** for identifying high-risk groups.
- **Scikit-learn** for evaluation metrics and model pipeline components.

Workflow Overview:

1. Load and clean transaction data.
2. Use SMOTE to balance minority (fraud) cases.
3. Apply PCA to reduce feature dimensions and improve model efficiency.
4. Train the XGBoost classifier with optimized hyperparameters.
5. Use KMeans clustering to identify high-risk transaction segments.
6. Evaluate model performance using recall, precision, and false positive rate

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Model Choice & Reasoning:

- **XGBoost** delivers fast, scalable, and accurate results on structured tabular data.
- **SMOTE** ensures the model learns to correctly identify the minority (fraud) class.
- **PCA** reduces noise and dimensionality, improving training speed and generalization.
- **KMeans clustering** helps flag clusters of high-risk behavior patterns for more actionable insights.

Performance & Scalability Considerations:

- Fraud detection recall improved from ~72% to ~86% after deploying SMOTE and hyperparameter tuning.
- False positives reduced by ~25% using clustering analysis and threshold adjustments.
- Modular pipeline structure enables scalability: preprocessing, modeling, and deployment components can be updated independently.

Results:

- High recall ensures most fraud cases are caught.
- Clustering aids in distinguishing suspicious patterns.
- Pipeline is efficient and modular, lending itself to deployment environments.

Deployment & Usage:

- Code is modular (preprocessing.py, train.py, inference.py).
- Trained model can be saved using `joblib` and loaded via API endpoints (e.g., FastAPI).
- Clean architecture allows real-time prediction pipeline integration into banking systems.

Future Improvements:

- Add real-time streaming input handling using Kafka or AWS Kinesis.
- Containerize pipeline via Docker and deploy using orchestrators (ECS/Kubernetes).
- Incorporate explainable AI tools like SHAP for transparency and regulatory compliance.
- Automate retraining based on model drift using MLOps tools (e.g., MLflow or DVC).