DSA 610 Redesign, Lecture 9 Outline

Lecture Outline: The Relationship of Databases to Data Warehouses, Data Marts, and Data Lakes Duration: 50 minutes

1. Introduction (5 minutes)

- **Objective:** Understand the general relationship and purpose of databases, data warehouses, data marts, and data lakes.
- Content:
 - **Definition**:
 - **Databases:** Systems for storing and managing structured data.
 - **Data Warehouses:** Centralized repositories for integrating and analyzing large volumes of structured data.
 - Data Marts: Subsets of data warehouses, tailored to specific business areas.
 - **Data Lakes:** Storage repositories that handle large volumes of structured and unstructured data.

2. Databases (10 minutes)

- **Objective:** Understand the role and functionality of traditional databases.
- Content:
 - **Definition:**
 - **Databases:** Systems that store and manage structured data using tables, rows, and columns.
 - Types:
 - Relational Databases (RDBMS): Use structured query language (SQL) (e.g., MySQL, PostgreSQL).
 - **NoSQL Databases:** Handle unstructured or semi-structured data (e.g., MongoDB, Cassandra).
 - Pros:
 - ACID Transactions: Ensure data integrity and consistency.
 - Efficient Querying: Support complex queries and transactions.
 - Cons:
 - Scalability Issues: Can struggle with very large datasets or high transaction volumes.
 - Schema Rigidity: Require predefined schemas which may not be flexible.

3. Data Warehouses (10 minutes)

- **Objective:** Understand the purpose and features of data warehouses.
- Content:
 - **Definition**:
 - Data Warehouses: Centralized systems for collecting and consolidating data from various sources for analysis and reporting.
 - Key Features:
 - **ETL Processes:** Extract, Transform, Load processes for data integration.
 - Data Modeling: Typically use star schema or snowflake schema for organizing data.
 - Pros:
 - Integrated Data: Centralized view of data from multiple sources.

- **Optimized for Query Performance:** Designed for complex queries and large-scale data analysis.
- Cons:
 - High Cost: Expensive to set up and maintain.
 - **Complexity:** Requires significant effort to design and implement.

4. Data Marts (10 minutes)

- **Objective:** Learn about the role of data marts and their relationship to data warehouses.
- Content:
 - **Definition:**
 - Data Marts: Specialized subsets of data warehouses, designed for specific business units or functions.
 - Key Features:
 - Focused Data: Tailored to the needs of specific departments (e.g., marketing, finance).
 - Faster Access: Provides quicker access to relevant data for users.
 - o **Pros:**
 - Ease of Use: Simplifies data access for specific business functions.
 - **Reduced Complexity:** Smaller scope compared to a full data warehouse.
 - Cons:
 - Data Silos: Can lead to isolated data stores if not well-integrated.
 - Limited Scope: May not provide a comprehensive view of all organizational data.

5. Data Lakes (10 minutes)

- **Objective:** Understand the characteristics and uses of data lakes.
- Content:
 - **Definition**:
 - **Data Lakes:** Storage repositories that handle vast amounts of raw, unstructured, and structured data.
 - Key Features:
 - Schema-on-Read: Flexible schema applied at the time of data retrieval.
 - Scalability: Designed to store large volumes of diverse data types.
 - Pros:
 - **Flexibility:** Accommodates various data types (structured, semi-structured, unstructured).
 - Scalable: Cost-effective storage for large datasets.
 - Cons:
 - Data Governance Challenges: Ensuring data quality and security can be complex.
 - **Performance Issues:** May require significant processing power for data retrieval and analysis.

6. Comparative Overview (5 minutes)

- **Objective:** Compare and contrast databases, data warehouses, data marts, and data lakes.
- Content:
 - Databases vs. Data Warehouses:
 - Databases: Transactional, structured, day-to-day operations.
 - Data Warehouses: Analytical, historical data, business intelligence.

- Data Warehouses vs. Data Marts:
 - Data Warehouses: Broad, enterprise-wide data integration.
 - Data Marts: Specific, departmental focus.
- Data Lakes vs. Data Warehouses:
 - Data Lakes: Raw data, high volume, and variety.
 - Data Warehouses: Processed, structured, and optimized for querying.

7. Q&A and Discussion (5 minutes)

- **Objective:** Address questions and discuss real-world applications of databases, data warehouses, data marts, and data lakes.
- Content:
 - **Q&A Session:** Open the floor for student questions.
 - **Discussion:** Explore how these systems are used in different industries and scenarios.

Key Takeaways

- **Databases:** Core systems for managing structured data.
- Data Warehouses: Centralized systems for large-scale data integration and analysis.
- Data Marts: Focused subsets of data warehouses for specific business needs.
- **Data Lakes:** Flexible storage solutions for diverse and large-scale data types.

Resources:

15 Types of Databases: <u>https://blog.algomaster.io/p/15-types-of-databases</u> What is a Datawarehouse?: <u>https://cloud.google.com/learn/what-is-a-data-warehouse</u> What is a Data Mart?: <u>https://aws.amazon.com/what-is/data-mart/</u> Intro to Data Lakes: <u>https://www.databricks.com/discover/data-lakes</u> Databases vs. Data warehouses vs. Data Lakes: <u>https://www.mongodb.com/resources/basics/databases/data-lake-vs-data-warehouse-vs-database</u> Data Mart vs. Data warehouse vs. Database vs. Data Lake: <u>https://www.zuar.com/blog/data-mart-vs-</u>

data-warehouse-vs-database-vs-data-lake/

Lecture Outline: The Importance of Domain Knowledge in Data Analysis and Tools for Data Analysis Duration: 50 minutes

1. Introduction (5 minutes)

- **Objective:** Understand the role of domain knowledge in data analysis and explore various tools for data analysis beyond spreadsheets, databases, and Python.
- Content:
 - **Definition:**
 - **Domain Knowledge:** Expertise and understanding of the specific field or industry related to the data being analyzed.
 - Scope:
 - Importance in Data Analysis
 - Tools Beyond Traditional Methods
 - Spatial and Graph/Network Data

2. Importance of Domain Knowledge in Data Analysis (15 minutes)

- Objective: Explore why domain knowledge is crucial for effective data analysis.
- Content:

- **1. Definition and Scope:**
 - **Domain Knowledge:** Insights and expertise about the specific context or field from which the data originates.
 - **Examples:** Healthcare, finance, retail, engineering.
- 2. Why It Matters:
 - Contextual Understanding:
 - Interpreting Data: Helps in making sense of data patterns and anomalies.
 - Relevance: Ensures that the analysis addresses relevant questions and issues.
 - Feature Selection:
 - Informed Choices: Guides the selection of relevant features and variables for analysis.
 - Model Interpretation:
 - **Meaningful Insights:** Aids in translating model results into actionable business insights.
- **3. Case Studies:**
 - Healthcare Analytics:
 - **Example:** Identifying factors influencing patient outcomes requires medical knowledge.
 - Financial Analysis:
 - **Example:** Understanding market trends and financial indicators requires knowledge of financial markets.

3. Tools for Data Analysis Beyond Spreadsheets, Databases, and Python (15 minutes)

- **Objective:** Learn about additional tools and platforms for data analysis.
- Content:

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- 1. Business Intelligence (BI) Tools:
 - Examples:
 - **Tableau:** Visualization and dashboarding.
 - **Power BI:** Interactive reports and data visualization.
 - Features:
 - User-Friendly Interfaces: Easy-to-use drag-and-drop functionalities.
 - Integration: Connects with various data sources for real-time analysis.
- **2. Statistical Software:**
 - Examples:
 - **R:** Advanced statistical analysis and visualization.
 - SAS: Complex data manipulation and statistical analysis.
 - Features:
 - **Specialized Libraries:** Extensive libraries for statistical techniques.
- **o 3.** Data Mining and Machine Learning Platforms:
 - Examples:
 - RapidMiner: Data preparation, machine learning, and model deployment.
 - KNIME: Data integration, processing, and analysis.
 - Features:
 - Visual Programming: GUI-based data processing and modeling.
- 4. Specialized Tools:

- Example:
 - **Gephi:** Network visualization and analysis.
 - **QGIS:** Geographic Information Systems (GIS) for spatial data analysis.
- Features:
 - Visualization: Advanced graph/network and spatial data analysis.

4. Spatial Data (10 minutes)

- **Objective:** Understand the concept and significance of spatial data in data analysis.
- Content:
 - 1. Definition and Importance:
 - **Spatial Data:** Data related to geographic locations and spatial relationships.
 - **Types:** Geographic coordinates, maps, satellite imagery.
 - 2. Tools and Techniques:
 - GIS Tools:
 - **QGIS:** Open-source GIS tool for spatial data analysis.
 - ArcGIS: Comprehensive suite for geographic data analysis.
 - Applications:
 - **Urban Planning:** Analyzing land use and infrastructure.
 - Environmental Studies: Monitoring and managing natural resources.
 - 3. Examples:
 - Heat Maps: Visualizing density and distribution of geographic phenomena.
 - Spatial Clustering: Identifying clusters or patterns in geographic data.

5. Graph/Network Data (10 minutes)

- **Objective:** Explore the analysis of graph and network data.
- Content:
 - **1. Definition and Importance:**
 - **Graph Data:** Data that represents relationships and connections between entities.
 - Network Data: Nodes (entities) and edges (relationships).
 - 2. Tools and Techniques:
 - Graph Visualization:
 - **Gephi:** Network visualization and analysis.
 - **Cytoscape:** Visualization and analysis of complex networks.
 - Graph Algorithms:
 - Centrality Measures: Identifying key nodes (e.g., PageRank).
 - Community Detection: Finding clusters or communities within a network.
 - **3. Examples:**
 - **Social Network Analysis:** Studying relationships and influence within social networks.
 - **Recommendation Systems:** Analyzing user-item interactions to provide recommendations.

6. Q&A and Discussion (5 minutes)

- Objective: Address questions and discuss practical applications of domain knowledge, tools, and data types.
- Content:

- **Q&A Session:** Open the floor for student questions.
- **Discussion:** Explore how domain knowledge and various tools can enhance data analysis in real-world scenarios.

Key Takeaways

- Domain Knowledge: Essential for meaningful data analysis and interpretation.
- Additional Tools: Business Intelligence tools, statistical software, data mining platforms, and specialized tools enhance data analysis capabilities.
- **Spatial and Graph/Network Data:** Specialized techniques and tools for analyzing geographic and relational data.

Resources:

The Importance of Domain Knowledge: <u>https://blog.ml.cmu.edu/2020/08/31/1-domain-knowledge/</u> Role of Domain Knowledge in Data Science: <u>https://www.geeksforgeeks.org/role-of-domain-knowledge-in-data-science/</u>

10 Data Analysis Tools and When to Use them: https://www.coursera.org/articles/data-analysis-tools Data Analysis in Excel: https://www.simplilearn.com/tutorials/excel-tutorial/data-analysis-excel 6 Databases for Analytics: https://www.toucantoco.com/en/blog/choosing-database-for-analytics Data Analysis with Python: https://www.toucantoco.com/en/blog/choosing-database-for-analytics Data Analysis with Python: https://www.geeksforgeeks.org/data-analysis-excel

Tableau for Analytics: https://www.tableau.com/analytics

Data Analysis in Power BI for Beginners: <u>https://k21academy.com/microsoft-azure/data-analyst/data-analysis-in-power-bi/</u>

R for Data Science: <u>https://r4ds.had.co.nz/introduction.html</u>

SAS: <u>https://guides.nyu.edu/sas</u>

SPSS: <u>https://researchcommons.library.ubc.ca/introduction-to-spss-for-statistical-analysis/</u>

Rapid Miner: <u>https://medium.com/image-processing-with-python/rapidminer-for-data-science-and-data-mining-1547bbc3b475</u>

KNIME: <u>https://www.knime.com/knime-analytics-platform</u>

Gephi Tutorial: <u>https://orgmapper.com/gephi-tutorial/</u>

QGIS Spatial Statistics:

https://docs.qgis.org/3.40/en/docs/training_manual/vector_analysis/spatial_statistics.html ArcGIS Analytics and Data Science: https://www.esri.com/en-us/arcgis/products/arcgispro/features/analytics-data-science

Cytoscape: https://cytoscape.org/what is cytoscape.html

MATLAB for Data Analysis: https://www.mathworks.com/products/matlab/data-analysis.html

Lecture Outline: Classification Methods in Python with Examples

Duration: 50 minutes

1. Introduction to Classification (5 minutes)

- **Objective:** Understand the concept of classification in machine learning and its applications.
- Content:
 - **Definition:** Classification is a supervised learning task where the goal is to predict the categorical label of new observations based on past observations.
 - **Examples:** Email spam detection, image recognition, medical diagnosis.

2. Overview of Classification Methods (10 minutes)

• **Objective:** Provide a brief overview of common classification methods.

- Content:
 - 1. Logistic Regression:
 - **Concept:** A linear model for binary classification problems.
 - 2. Decision Trees:
 - Concept: A tree-like model of decisions and their possible consequences.
 - 3. Random Forest:
 - **Concept:** An ensemble of decision trees to improve classification accuracy.
 - 4. Support Vector Machines (SVM):
 - Concept: Classifies data by finding the optimal hyperplane that separates classes.
 - 5. K-Nearest Neighbors (KNN):
 - **Concept:** Classifies based on the majority class among the k-nearest neighbors.
 - 6. Neural Networks:
 - **Concept:** Uses multiple layers to learn complex patterns in data.

3. Logistic Regression in Python (8 minutes)

- **Objective:** Implement and understand logistic regression for classification.
- Content:

```
• Using scikit-learn:
```

import pandas as pd

from sklearn.model_selection import train_test_split from sklearn.linear_model import LogisticRegression from sklearn.metrics import accuracy_score, confusion_matrix

```
# Example dataset
data = {
  'Feature1': [1, 2, 3, 4, 5],
  'Feature2': [2, 4, 6, 8, 10],
  'Label': [0, 0, 1, 1, 1]
}
df = pd.DataFrame(data)
X = df[['Feature1', 'Feature2']]
y = df['Label']
# Split data
X train, X test, y train, y test = train test split(X, y, test size=0.2, random state=42)
# Train model
model = LogisticRegression()
model.fit(X_train, y_train)
# Predictions
y_pred = model.predict(X_test)
```

```
# Evaluation
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

4. Decision Trees and Random Forests (8 minutes)

- **Objective:** Implement and understand decision trees and random forests for classification.
- Content:

• Using scikit-learn:

from sklearn.tree import DecisionTreeClassifier from sklearn.ensemble import RandomForestClassifier

Decision Tree dt_model = DecisionTreeClassifier() dt_model.fit(X_train, y_train) dt_pred = dt_model.predict(X_test) print("Decision Tree Accuracy:", accuracy_score(y_test, dt_pred)) print("Decision Tree Confusion Matrix:\n", confusion_matrix(y_test, dt_pred))

Random Forest
rf_model = RandomForestClassifier(n_estimators=100)
rf_model.fit(X_train, y_train)
rf_pred = rf_model.predict(X_test)
print("Random Forest Accuracy:", accuracy_score(y_test, rf_pred))
print("Random Forest Confusion Matrix:\n", confusion_matrix(y_test, rf_pred))

Using xgboost:

import xgboost as xgb from xgboost import XGBClassifier

XGBoost
xgb_model = XGBClassifier()
xgb_model.fit(X_train, y_train)
xgb_pred = xgb_model.predict(X_test)
print("XGBoost Accuracy:", accuracy_score(y_test, xgb_pred))
print("XGBoost Confusion Matrix:\n", confusion_matrix(y_test, xgb_pred))

5. Support Vector Machines (SVM) (8 minutes)

- **Objective:** Implement and understand SVM for classification.
- Content:
 - Using scikit-learn:

from sklearn.svm import SVC

SVM
svm_model = SVC(kernel='linear')
svm_model.fit(X_train, y_train)
svm_pred = svm_model.predict(X_test)
print("SVM Accuracy:", accuracy_score(y_test, svm_pred))
print("SVM Confusion Matrix:\n", confusion_matrix(y_test, svm_pred))

6. K-Nearest Neighbors (KNN) (8 minutes)

- **Objective:** Implement and understand KNN for classification.
- Content:
 - Using scikit-learn:

from sklearn.neighbors import KNeighborsClassifier

KNN knn_model = KNeighborsClassifier(n_neighbors=3) knn_model.fit(X_train, y_train) knn_pred = knn_model.predict(X_test) print("KNN Accuracy:", accuracy_score(y_test, knn_pred)) print("KNN Confusion Matrix:\n", confusion_matrix(y_test, knn_pred))

7. Neural Networks (8 minutes)

- **Objective:** Implement and understand neural networks for classification.
- Content:

• Using Keras with TensorFlow:

from tensorflow.keras.models import Sequential from tensorflow.keras.layers import Dense

```
# Neural Network
nn_model = Sequential([
    Dense(10, activation='relu', input_shape=(X_train.shape[1],)),
    Dense(1, activation='sigmoid')
])
```

nn_model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
nn_model.fit(X_train, y_train, epochs=10, verbose=1)
nn_loss, nn_accuracy = nn_model.evaluate(X_test, y_test)
print("Neural Network Accuracy:", nn_accuracy)

8. Q&A and Discussion (5 minutes)

- Objective: Address questions and discuss practical considerations for choosing classification methods.
- Content:
 - **Q&A Session:** Open the floor for student questions.
 - **Discussion:** Explore when to use different classification methods based on the data and problem context.

Key Takeaways

- **Classification Methods:** Overview of various classification techniques including logistic regression, decision trees, random forests, SVM, KNN, and neural networks.
- **Python Libraries:** Practical examples using scikit-learn, xgboost, and keras for implementing these methods.

• **Model Evaluation:** Importance of evaluating model performance using metrics like accuracy and confusion matrices.

Resources:

Classification in Machine Learning: https://www.datacamp.com/blog/classification-machine-learning Logistic Regression in Python: https://www.geeksforgeeks.org/ml-logistic-regression-using-python/ Decision Trees: <u>https://scikit-learn.org/stable/modules/tree.html</u> Random Forest Classifier: https://www.geeksforgeeks.org/random-forest-classifier-using-scikit-learn/ Support Vector Machines: https://scikit-learn.org/stable/modules/svm.html KNN classifier: https://www.w3schools.com/python/python ml knn.asp Binary Classification: https://www.learndatasci.com/glossary/binary-classification/ Multi-class Classification: https://www.geeksforgeeks.org/multiclass-classification-using-scikit-learn/ Multi-label Classification: https://www.kdnuggets.com/2023/08/multilabel-classification-introductionpython-scikitlearn.html Naive Bayes: https://www.datacamp.com/tutorial/naive-bayes-scikit-learn Gradient Boost: https://scikitlearn.org/stable/modules/generated/sklearn.ensemble.GradientBoostingClassifier.html Neural Networks: https://scikit-learn.org/stable/modules/neural networks supervised.html ROC & AUC: https://developers.google.com/machine-learning/crash-course/classification/roc-and-auc Confusion Matrix: https://www.geeksforgeeks.org/confusion-matrix-machine-learning/ Classification Metrics: https://www.analyticsvidhya.com/blog/2021/07/metrics-to-evaluate-yourclassification-model-to-take-the-right-decisions/