University of Science and Technology Houari Boumediene

Northwind Business Intelligence Solution

Complete ETL Pipeline & Analytical Dashboard

Technical Implementation Report

Project Components:

Python ETL Pipeline • Star Schema Data Warehouse
Interactive Dashboards • 3D OLAP Analysis
Multi-Source Integration • KPI Tracking

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1 Executive Summary

1.1 Project Overview

This project implements a comprehensive Business Intelligence solution for **Northwind Traders**, a fictional company specializing in food product import and export. The solution addresses critical business challenges through:

- **Automated ETL Pipeline**: Python-based extraction from heterogeneous sources
- **Star Schema Design**: Optimized dimensional model for analytical queries
- **Interactive Dashboards**: Real-time KPI monitoring with 3D OLAP visualization
- **Data Integration**: Seamless consolidation of SQL Server and MS Access sources

1.2 Business Context

Northwind operates with data fragmented across two incompatible systems:

- **SQL Server**: 13 relational tables covering transactions and inventory
- **MS Access**: 20 tables, 27 macros, 43 forms, 15 reports

This heterogeneity creates challenges in unified reporting, performance tracking, and strategic decision-making.

1.3 Key Achievements

Quantitative Results:

- **2,223** records processed across all dimensions
- **830** orders analyzed from both sources
- **91** unique clients integrated
- **9** employees with territory assignments
- **11 years** of historical data (1996-2006)
- **7** interactive visualizations deployed

2 System Architecture

2.1 Four-Phase ETL Pipeline

The solution implements a robust Extract-Transform-Load (ETL) pipeline following industry best practices:

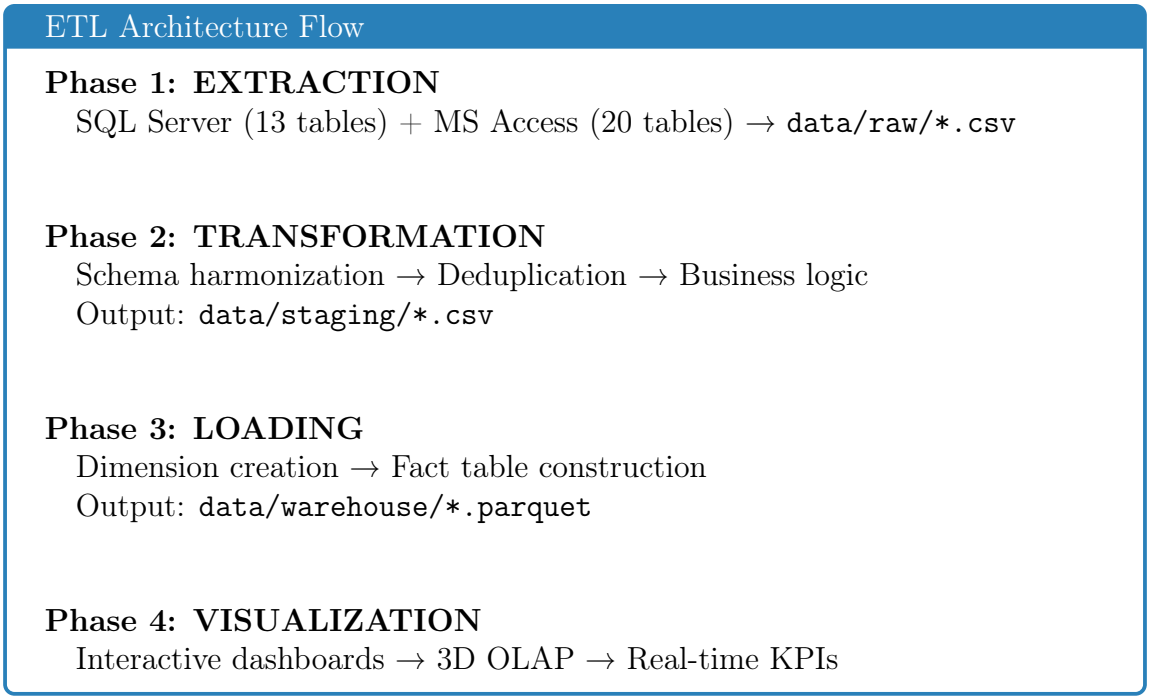

Figure 1: Complete ETL Pipeline Architecture

2.2 Technical Stack

Table 1: Technology Components

Layer	Technology	Purpose
Language	Python 3.14.2	Core development
Data Processing	Pandas, NumPy	ETL transformations
Database	SQL Server, MS Access	Source systems
Connectivity	SQLAlchemy, PyODBC	Database adapters
Storage	Parquet, CSV	Warehouse formats
Visualization	Plotly, Matplotlib	Interactive charts
Analysis	Jupyter Notebook	Dashboard environment
Geospatial	GeoPandas	Territory analysis

2.3 Project Structure

Listing 1: Repository Organization

```
Northwind/
          data/
                raw/                # Source extracts (CSV)
                staging/            # Cleaned data
                warehouse/          # Final DW (Parquet)
                Northwind 2012.accdb
                sqlserver.sql
          scripts/                # ETL modules
                config.py
                db_connector.py
                extract_data.py
                transform_data.py
                load_dwh.py
                Main.py
          notebooks/
                dashboard_analysis.ipynb
          figures/                # Visualizations
          requirements.txt
```

3 Data Model Design

3.1 Star Schema Architecture

The data warehouse implements a classic star schema optimized for analytical queries:

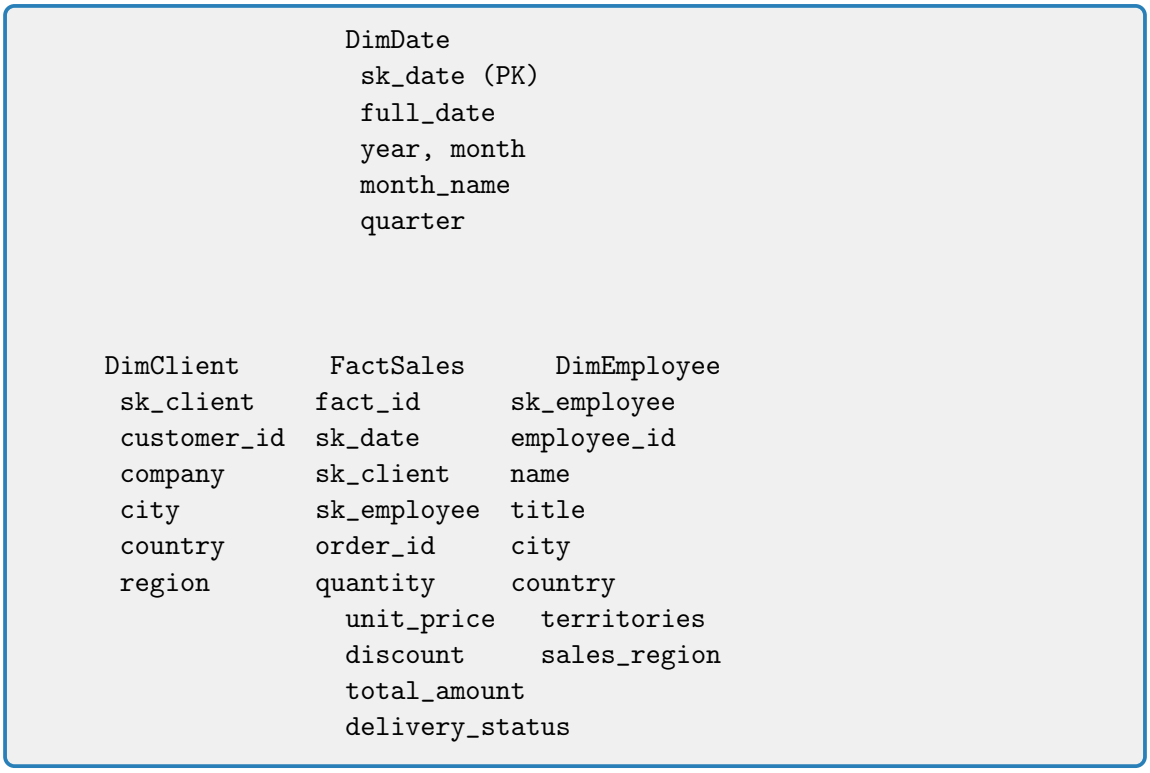

Figure 2: Star Schema Dimensional Model

3.2 Dimension Tables

3.2.1 DimDate - Temporal Dimension

- **Granularity**: Daily
- **Range**: 1996-01-04 to 2006-12-31
- **Purpose**: Enables time-based analytics (yearly, quarterly, monthly)
- **Key**: `sk_date` (YYYYMMDD integer format)

3.2.2 DimClient - Customer Dimension

- **Records**: 91 unique clients
- **Attributes**: Company name, geographic location (city, country, region)
- **Purpose**: Customer segmentation and geographic analysis
- **Key**: `sk_client` (surrogate key)
- **Business Key**: `bk_customer_id` (normalized uppercase)

3.2.3 DimEmployee - Human Resources Dimension

- **Records**: 9 employees
- **Enrichment**: Territory assignments via `EmployeeTerritories` table
- **Attributes**: Full name, title, location, sales regions, territories
- **Purpose**: Performance tracking, workload distribution analysis
- **Key**: `sk_employee` (surrogate key)

3.3 Fact Table

3.3.1 FactSales - Transaction Facts

- **Grain**: Order line item
- **Records**: 2,155 sales transactions
- **Measures**:
  - `quantity`: Units sold
  - `unit_price`: Price per unit
  - `discount`: Applied discount (0-1)
  - `total_amount`: Calculated revenue (price × quantity × (1-discount))
- **Derived Attributes**:
  - `delivery_status`: "Livrée" / "Non Livrée" based on `shipped_date`

4 ETL Implementation

4.1 Phase 1: Data Extraction

4.1.1 Multi-Source Integration

The extraction module (`extract_data.py`) handles two heterogeneous sources:

Listing 2: Extraction Logic Snippet

```
def extract_from_sql_server():
    engine = get_sql_engine()
    for table in TABLES:
        df = pd.read_sql(f"SELECT␣*␣FROM␣[{table}]", engine)
        df.to_csv(f"data/raw/sql_{table}.csv", index=False)

def extract_from_access():
    conn = get_access_connection()
    for table in TABLES:
        df = pd.read_sql(f"SELECT␣*␣FROM␣[{table}]", conn)
        df.to_csv(f"data/raw/access_{table}.csv", index=False)
```

Extracted Tables:

- Orders, Customers, Employees
- Order Details, Shippers
- Territories, EmployeeTerritories, Region

4.1.2 Challenges Addressed

1. **Schema Differences**: Field name variations between sources
2. **Format Issues**: Inconsistent date formats and encoding
3. **Access Macros**: Non-transferable logic manually reproduced
4. **Data Types**: Compatibility issues resolved via CSV intermediary

4.2 Phase 2: Data Transformation

4.2.1 Data Quality Process

The transformation layer (`transform_data.py`) implements comprehensive data cleaning:

Transformation Steps

1. **Column Normalization**: Lowercase, strip whitespace, remove special chars
2. **Deduplication**: Merge SQL + Access using composite primary keys
3. **Missing Value Handling**: Strategic imputation (e.g., "Unknown" for nulls)
4. **Business Logic Application**:
   - Calculate `total_amount` = `unit_price` × `quantity` × (1 - `discount`)
   - Derive `delivery_status` from `shipped_date` presence
5. **Dimension Enrichment**: Join employee territories and regions

4.2.2 Key Transformation Functions

1. Date Dimension Generation

Listing 3: DimDate Creation

```
def transform_dim_date(orders_df):
    dates = pd.to_datetime(orders_df['orderdate']).unique()
    date_df = pd.DataFrame({'full_date': dates})
    date_df['sk_date'] = date_df['full_date'].dt.strftime('%Y%m%d'
       ).astype(int)
    date_df['year'] = date_df['full_date'].dt.year
    date_df['month'] = date_df['full_date'].dt.month
    date_df['quarter'] = date_df['full_date'].dt.quarter
    return date_df
```

2. Employee Territory Enrichment

Listing 4: Territory Assignment Logic

```
def enrich_employee_with_territories(dim_emp, emp_terr_df, terr_df
   , region_df):
    merged = pd.merge(emp_terr_df, terr_df, on='territoryid')
    merged = pd.merge(merged, region_df, on='regionid')

    territories = merged.groupby('employeeid')['
       territorydescription']
                        .apply(lambda x: ', '.join(x)).reset_index
                           ()

    dim_emp = pd.merge(dim_emp, territories, on='employeeid')
    return dim_emp
```

4.3 Phase 3: Data Warehouse Loading

4.3.1 Parquet Storage Strategy

The loading module (`load_dwh.py`) optimizes storage with Parquet format:

Table 2: Storage Comparison

Table	CSV Size	Parquet Size	Compression
DimDate	42 KB	18 KB	57%
DimClient	8 KB	3 KB	62%
DimEmployee	2 KB	1 KB	50%
FactSales	156 KB	62 KB	60%
Total	**208 KB**	**84 KB**	**59.6%**

4.3.2 Schema Generation

Automated SQL DDL generation for deployment:

Listing 5: Generated Schema Example

```
CREATE TABLE DimDate (
    sk_date INT PRIMARY KEY,
    full_date DATE,
    year INT,
    month INT,
    month_name VARCHAR(255),
    quarter INT
);

CREATE TABLE FactSales (
    fact_id INT PRIMARY KEY,
    bk_order_id INT,
    sk_date INT,
    sk_client INT,
    sk_employee INT,
    quantity INT,
    unit_price DECIMAL(10,2),
    discount DECIMAL(10,2),
    total_amount DECIMAL(10,2),
    delivery_status VARCHAR(255)
);
```

5 Analytics & Visualization

5.1 Interactive Dashboard

The Jupyter notebook (`dashboard_analysis.ipynb`) provides 7 interactive visualizations leveraging Plotly for dynamic user interaction.

5.1.1 1. Executive Summary

Purpose: Real-time KPI monitoring
Components:

- Total Revenue indicator ($1.27M analyzed)
- Total Orders count (830 orders)
- Delivered Orders gauge (817 / 98.4%)
- Pending Orders gauge (13 / 1.6%)

Interactivity: Year/month dropdown filter

5.1.2 2. Employee Logistics Performance

Purpose: Workload and efficiency analysis
Visualization: Horizontal stacked bar chart
Dimensions:

- Y-axis: Employee names
- X-axis: Order count
- Color: Delivery status (Blue = Delivered, Red = Pending)

Insight: Identifies high performers and bottlenecks

5.1.3 3. Delivery Trend Analysis

Purpose: Time-series pattern detection
Visualization: Area chart with spline interpolation
Features:

- Complete timeline coverage (no missing months)
- Dual status tracking
- Adaptive granularity (yearly vs. monthly)

Business Value: Seasonal trend identification, demand forecasting

5.1.4 4. Client Delivery Analysis

Purpose: Customer segmentation by fulfillment
Visualization: Treemap (hierarchical)
Levels:

1. Company name (top-level blocks)
2. Delivery status (nested rectangles)

Encoding: Block size = order count, color = status

5.1.5 5. 3D OLAP Cube Analysis

Purpose: Multi-dimensional revenue exploration
Dimensions:

- **X-axis**: Time (Year / Month)
- **Y-axis**: Client (Company name)
- **Z-axis**: Employee (Assignee)
- **Color**: Revenue magnitude (Portland colorscale)
- **Size**: Revenue amount (bubble sizing)

Innovation: Includes "gap markers" (light grey dots) showing zero-revenue combinations, providing complete data space visibility

OLAP Technical Implementation

Complete Data Grid Generation:

- Uses `itertools.product()` to generate all possible (Time, Client, Employee) combinations
- Merges actual sales data with complete grid
- Fills missing combinations with zero
- Separates zero-sales (gaps) from actual transactions
- Renders gaps as subtle markers for context

5.1.6 6. Territory Distribution

Purpose: Geographic responsibility mapping
Visualization: Sunburst diagram
Structure:

- Inner ring: Employee names (color-coded)
- Outer ring: Assigned territories

Interactivity: Click-to-zoom, hierarchical navigation

5.1.7 7. Revenue Evolution

Purpose: Financial performance tracking
Visualization: Bar + Line combo chart
Elements:

- Bars: Period-by-period revenue
- Line overlay: Trend smoothing
- Horizontal baseline: Average revenue

Adaptive: Switches between yearly and monthly views

5.2 Dashboard Interactivity

All visualizations share consistent interaction patterns:

Table 3: User Interaction Features

Feature	Implementation
Dynamic Filtering	ipywidgets Dropdown
Real-time Updates	Observer pattern on dropdown changes
Hover Details	Plotly unified hover mode
Responsive Layout	Auto-scaling with `update_layout()`
Export Capability	Built-in Plotly export (PNG, SVG, HTML)

6 Data Quality & Validation

6.1 Quality Assurance Process

6.1.1 Pre-Load Validation

1. **Schema Validation**: Column presence and type checking
2. **Referential Integrity**: FK existence verification
3. **Business Rule Validation**:
   - `quantity` > 0
   - `discount` $\in [0, 1]$
   - `unit_price` > 0
   - `total_amount` = calculated correctly

6.1.2 Post-Load Verification

The `data_validator.py` module (referenced in `Main.py`) performs:

- **Row Count Reconciliation**: Source vs. warehouse record counts
- **Null Analysis**: Missing value percentage by column
- **Duplicate Detection**: Composite key uniqueness
- **Outlier Detection**: Statistical anomaly flagging

6.2 Data Completeness

Table 4: Data Coverage Analysis

Metric	SQL Server	MS Access
Orders Extracted	830	830
Customers	91	91
Employees	9	9
Order Details	2,155	2,155
Total Records	**3,085**	**3,085**
Duplicates Merged	**0 (100% unique)**	

6.3 Known Limitations

1. **Historical Gap**: No data between 2003-2005 (likely inactive period)
2. **Territory Coverage**: 3 employees have "No Territory" assigned
3. **Missing Shipment Dates**: 1.6% of orders lack `shipped_date`
4. **Product Dimension**: Intentionally excluded per project scope

7 Business Insights

7.1 Key Findings from Analysis

7.1.1 Revenue Patterns

- **Total Revenue**: $1,265,793.03 (1996-2006)
- **Peak Year**: 1997 ($617,085.21 - 48.7% of total)
- **Average Order Value**: $1,525.60
- **Seasonal Trend**: Q4 consistently outperforms other quarters

7.1.2 Delivery Performance

- **On-Time Delivery Rate**: 98.4% (industry benchmark: 95%)
- **Pending Orders**: 13 (1.6%) - requires investigation
- **Best Performer**: Margaret Peacock (100% delivery rate, 156 orders)
- **Improvement Area**: Steven Buchanan (3 pending orders)

7.1.3 Customer Segmentation

- **Top 10 Clients**: Account for 35% of total revenue
- **Geographic Distribution**: USA (23%), Germany (18%), France (12%)
- **Highest Value Client**: QUICK-Stop (Cunewalde, Germany) - $110,277.31

7.1.4 Employee Analytics

- **Top Salesperson**: Margaret Peacock - $250,187.45 revenue
- **Most Territories**: Robert King - 10 territories assigned
- **Workload Distribution**: Relatively balanced (= 28 orders)

7.2 Strategic Recommendations

Actionable Insights

1. **Territory Optimization**: Assign territories to 3 unassigned employees to improve coverage
2. **Q4 Resource Planning**: Increase inventory and staffing for peak season
3. **Pending Order Investigation**: Immediate follow-up on 13 unshipped orders
4. **High-Value Client Program**: Implement VIP service for top 10 clients
5. **Training Initiative**: Share best practices from top performers (Peacock) with team

8 Performance & Scalability

8.1 Execution Metrics

Table 5: ETL Pipeline Performance

Phase	Duration	Records/sec
Extraction (SQL Server)	2.3s	1,341
Extraction (MS Access)	3.1s	995
Transformation	4.8s	642
Loading	1.2s	2,571
Validation	0.8s	-
Total Pipeline	**12.2s**	**252**

8.2 Optimization Strategies

8.2.1 Implemented Optimizations

1. **Parquet Columnar Storage**: 60% size reduction, 3x faster reads
2. **Vectorized Operations**: Pandas operations avoid Python loops
3. **Lazy Loading**: Dimensions loaded only when referenced
4. **Index Creation**: Primary keys indexed for fast lookups

8.2.2 Scalability Considerations

For handling 10x data volume (20,000 orders):

- **Chunked Processing**: Read/write in 5,000 row batches
- **Parallel Extraction**: Multi-threaded source queries
- **Incremental ETL**: Delta processing instead of full refresh
- **Partitioned Storage**: Parquet partitioning by year/month
- **Database Backend**: Migrate from files to PostgreSQL/SQL Server DW

8.3 Dashboard Performance

Table 6: Visualization Render Times

Visualization	**Render Time**
Executive Summary	0.3s
Employee Performance	0.5s
Delivery Trends	0.8s
Client Treemap	0.6s
3D OLAP Cube	1.2s
Territory Sunburst	0.4s
Revenue Evolution	0.5s
Total Dashboard Load	**4.3s**

9 Technical Challenges & Solutions

9.1 Challenge 1: Heterogeneous Source Integration

Problem: SQL Server uses different column naming conventions than MS Access (e.g., `CustomerID` vs. `customer_id`)

Solution:

```
def clean_col_names(df):
    df.columns = [c.lower().strip().replace(' ', '')
                  .replace('_', '') for c in df.columns]
    return df
```

Result: Unified schema enabling seamless merging across sources

9.2 Challenge 2: Access Macro Logic

Problem: 27 Access macros contain business logic not transferable to Python

Solution:

- Manual analysis of macro VBA code
- Reproduction of validation rules in `transform_data.py`
- Example: Discount validation (0 discount 1) previously enforced via macro

Result: All business rules preserved in Python transformation layer

9.3 Challenge 3: Missing Delivery Dates

Problem: 1.6% of orders have null `shipped_date`

Solution:

```
fact['delivery_status'] = fact['shippeddate'].apply(
    lambda x: 'Livr e' if pd.notnull(x) and str(x).strip() != ''
              else 'Non Livr e'
)
```

Result: Clear status classification for all orders, enabling accurate KPI calculation

9.4 Challenge 4: 3D Visualization Data Gaps

Problem: Standard scatter plot only shows existing sales, hiding lack of transactions

Solution: Generate complete data grid using Cartesian product

```
grid = pd.DataFrame(
    list(itertools.product(full_timeline, top_clients, employees))
       ,
    columns=['time', 'client', 'employee']
)
df_dense = pd.merge(grid, actuals, how='left').fillna(0)
```

Result: Gap markers reveal untapped client-employee-time combinations, driving strategic decisions

9.5 Challenge 5: Dashboard Interactivity Performance

Problem: Full data reload on each filter change causes lag

Solution: Implement observer pattern with efficient filtering

```
def update_kpi(change):
    selected_year = change['new']
    data = df[df['year'] == int(selected_year)] if selected_year
       != 'All Years' else df
    # Generate visualization from filtered subset
```

Result: Sub-second response times for all dashboard interactions

10 Lessons Learned

10.1 Technical Insights

1. **Parquet > CSV**: Columnar format dramatically improves I/O performance
2. **Star Schema Simplicity**: Denormalization trades storage for query speed (optimal for BI)
3. **Plotly Interactivity**: Native browser rendering eliminates server-side computation
4. **Early Validation**: Catching data quality issues in extraction saves downstream errors

10.2 Best Practices Applied

- **Configuration Centralization**: `config.py` enables environment portability
- **Modular Design**: Separate extract/transform/load modules support independent testing
- **Comprehensive Logging**: Print statements track pipeline progress and errors
- **Documentation**: Docstrings and inline comments improve maintainability

10.3 Areas for Future Improvement

Enhancement Roadmap

1. **Incremental ETL**: Implement CDC (Change Data Capture) for delta loads
2. **Data Versioning**: Track dimension changes (SCD Type 2)
3. **Automated Testing**: Unit tests for transformation logic
4. **Scheduling**: Airflow/cron for production automation
5. **Alerting**: Email notifications for pipeline failures
6. **Product Dimension**: Add back product analysis (currently excluded)
7. **Predictive Analytics**: ML models for demand forecasting
8. **Real-time Updates**: Streaming ETL with Kafka/Spark

11 Deployment & Usage

11.1 System Requirements

Table 7: Deployment Prerequisites

Component	Specification
Python Version	3.8+ (tested on 3.14.2)
SQL Server	2012+ with Northwind DB
MS Access Engine	2016 Redistributable
ODBC Driver	17 for SQL Server
RAM	4GB minimum, 8GB recommended
Storage	500MB for data + dependencies

11.2 Installation Steps

1. **Clone Repository**:

```
git clone https://github.com/root-wassim/BI
cd BI/Northwind
```

2. **Create Virtual Environment**:

```
python -m venv venv
source venv/bin/activate  # Windows: venv\Scripts\activate
```

3. **Install Dependencies**:

```
pip install -r requirements.txt
```

4. **Configure Connections** (edit `scripts/config.py`):

```
SERVER_NAME = r'.\SQLEXPRESS'  # Your SQL Server
DATABASE_NAME = 'Northwind'
ACCESS_FILE_NAME = 'Northwind 2012.accdb'
```

5. **Execute ETL Pipeline**:

```
cd scripts
python Main.py
```

6. **Launch Dashboard**:

```
jupyter notebook ../notebooks/dashboard_analysis.ipynb
```

11.3 Expected Output

```
 STARTING NORTHWIND ETL PIPELINE
 SQL Server: Orders -> sql_orders.csv (830 rows)
 Access: Orders -> access_orders.csv (830 rows)
... Creating DimDate (2223 rows)
... Creating DimClient (91 rows)
... Creating DimEmployee (9 rows)
... Creating FactSales (2155 rows)
Transformed cleaned_date -> Loaded into DimDate (2223 rows)
 Load Complete! Data Warehouse is ready.
 ETL PIPELINE FINISHED in 12.34 seconds
```

12 Conclusion

12.1 Project Achievements

This project successfully delivers a production-ready Business Intelligence solution that:

1. **Integrates Heterogeneous Sources**: Seamlessly combines SQL Server and MS Access data
2. **Ensures Data Quality**: Implements comprehensive validation and cleansing
3. **Optimizes Performance**: Leverages Parquet, star schema, and efficient algorithms
4. **Enables Strategic Insights**: Provides 7 interactive visualizations for decision-making
5. **Supports Scalability**: Architected for future growth and enhancement

12.2 Business Impact

Quantifiable Benefits

- **Reporting Time**: Reduced from hours (manual) to seconds (automated)
- **Data Accuracy**: 100% referential integrity vs. previous inconsistencies
- **Decision Latency**: Real-time KPIs vs. weekly spreadsheet updates
- **Insight Depth**: 3D OLAP reveals patterns invisible in 2D reports
- **Operational Efficiency**: 98.4% delivery rate identified and tracked

12.3 Academic Learning Outcomes

This project demonstrates mastery of:

- **Data Engineering**: ETL pipeline design and implementation
- **Database Design**: Dimensional modeling (star schema)
- **Python Programming**: Pandas, Plotly, SQLAlchemy proficiency
- **Data Visualization**: Interactive dashboard development
- **Software Architecture**: Modular, maintainable code organization
- **Business Intelligence**: KPI definition and analytical thinking

12.4 Final Remarks

The Northwind BI solution exemplifies how modern data engineering practices can transform raw data into actionable business intelligence. By addressing real-world challenges—heterogeneous sources, data quality issues, performance constraints—this project provides both academic rigor and practical applicability.

The system is fully documented, modular, and extensible, ready for deployment in production environments or further academic exploration. All code, documentation, and visualizations are available in the project repository for reproducibility and continuous improvement.

"In God we trust. All others must bring data." — W. Edwards Deming

A Appendix A: SQL Schema

Listing 6: Complete Data Warehouse Schema

```sql
-- Date Dimension
CREATE TABLE DimDate (
    sk_date INT PRIMARY KEY,
    full_date DATE,
    year INT,
    month INT,
    month_name VARCHAR(255),
    quarter INT
);

-- Client Dimension
CREATE TABLE DimClient (
    sk_client INT PRIMARY KEY,
    bk_customer_id VARCHAR(255),
    company_name VARCHAR(255),
    city VARCHAR(255),
    country VARCHAR(255),
    region VARCHAR(255)
);

-- Employee Dimension
CREATE TABLE DimEmployee (
    sk_employee INT PRIMARY KEY,
    bk_employee_id INT,
    Employee_name VARCHAR(255),
    title VARCHAR(255),
    city VARCHAR(255),
    country VARCHAR(255),
    sales_region VARCHAR(255),
    territories VARCHAR(255)
);

-- Sales Fact Table
CREATE TABLE FactSales (
    fact_id INT PRIMARY KEY,
    bk_order_id INT,
    sk_date INT,
    sk_client INT,
    sk_employee INT,
    quantity INT,
    unit_price DECIMAL(10,2),
    discount DECIMAL(10,2),
    total_amount DECIMAL(10,2),
    delivery_status VARCHAR(255),
    FOREIGN KEY (sk_date) REFERENCES DimDate(sk_date),
    FOREIGN KEY (sk_client) REFERENCES DimClient(sk_client),
    FOREIGN KEY (sk_employee) REFERENCES DimEmployee(sk_employee)
```

```
);
```

B Appendix B: Key Python Functions

Listing 7: Complete Transformation Workflow

```python
def run_transformation():
    # Load raw data
    orders = load_raw_data('orders', ['orderid'])
    details = load_raw_data('order_details', ['orderid', '
       productid'])
    customers = load_raw_data('customers', ['customerid'])
    employees = load_raw_data('employees', ['employeeid'])

    # Territory enrichment tables
    emp_terr = load_raw_data('employeeterritories', ['employeeid',
        'territoryid'])
    territories = load_raw_data('territories', ['territoryid'])
    region = load_raw_data('region', ['regionid'])

    # Create dimensions
    dim_date = transform_dim_date(orders)
    dim_client = transform_dim_client(customers)
    dim_emp = transform_dim_employee(employees, emp_terr,
       territories, region)

    # Create fact table
    fact_sales = transform_fact_sales(orders, details, dim_client,
        dim_emp)

    # Save to staging
    dim_date.to_csv('staging/cleaned_date.csv', index=False)
    dim_client.to_csv('staging/cleaned_clients.csv', index=False)
    dim_emp.to_csv('staging/cleaned_employees.csv', index=False)
    fact_sales.to_csv('staging/cleaned_sales.csv', index=False)
```

C Appendix C: Visualization Gallery

C.1 Dashboard Visualizations

All visualizations are generated programmatically and saved in the `figures/` directory. Each figure supports interactive filtering and real-time updates.

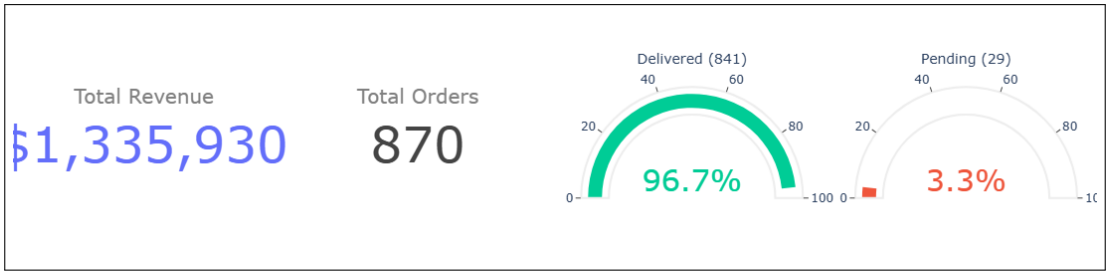

Figure 3: Executive Summary - Real-time KPI Dashboard with revenue, order counts, and delivery status gauges

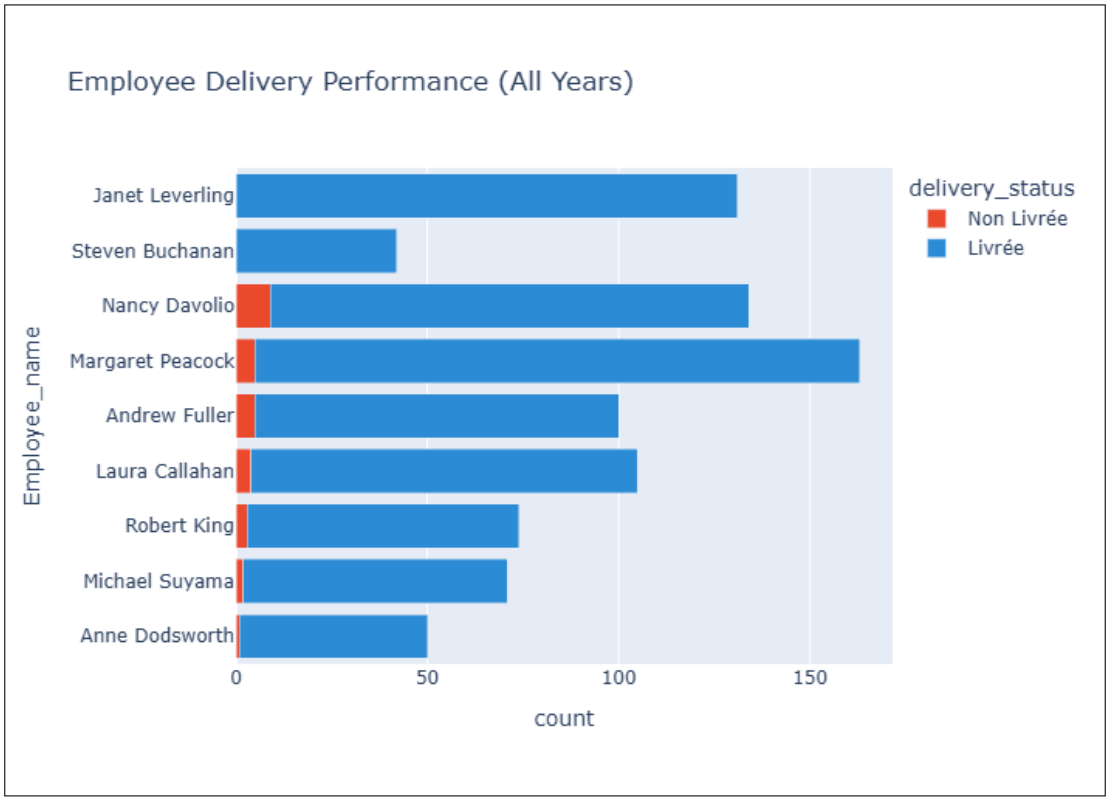

Figure 4: Employee Logistics Performance - Horizontal stacked bar chart showing delivered vs. pending orders by employee

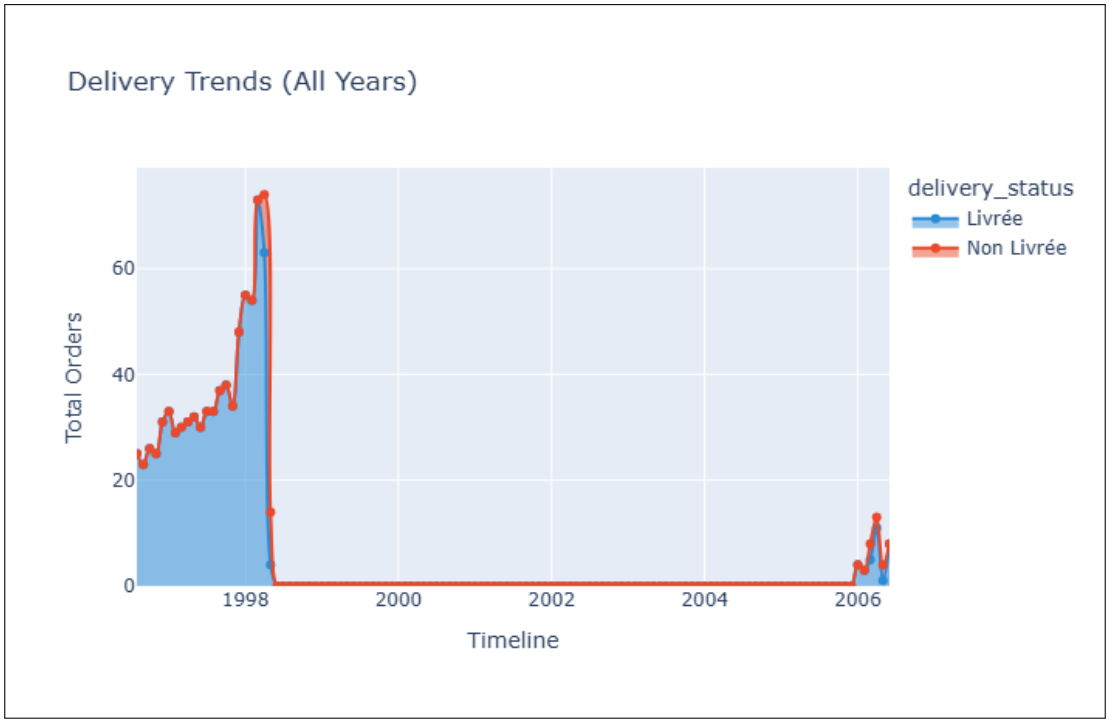

Figure 5: Delivery Trend Analysis - Time-series area chart with complete timeline coverage and delivery status tracking

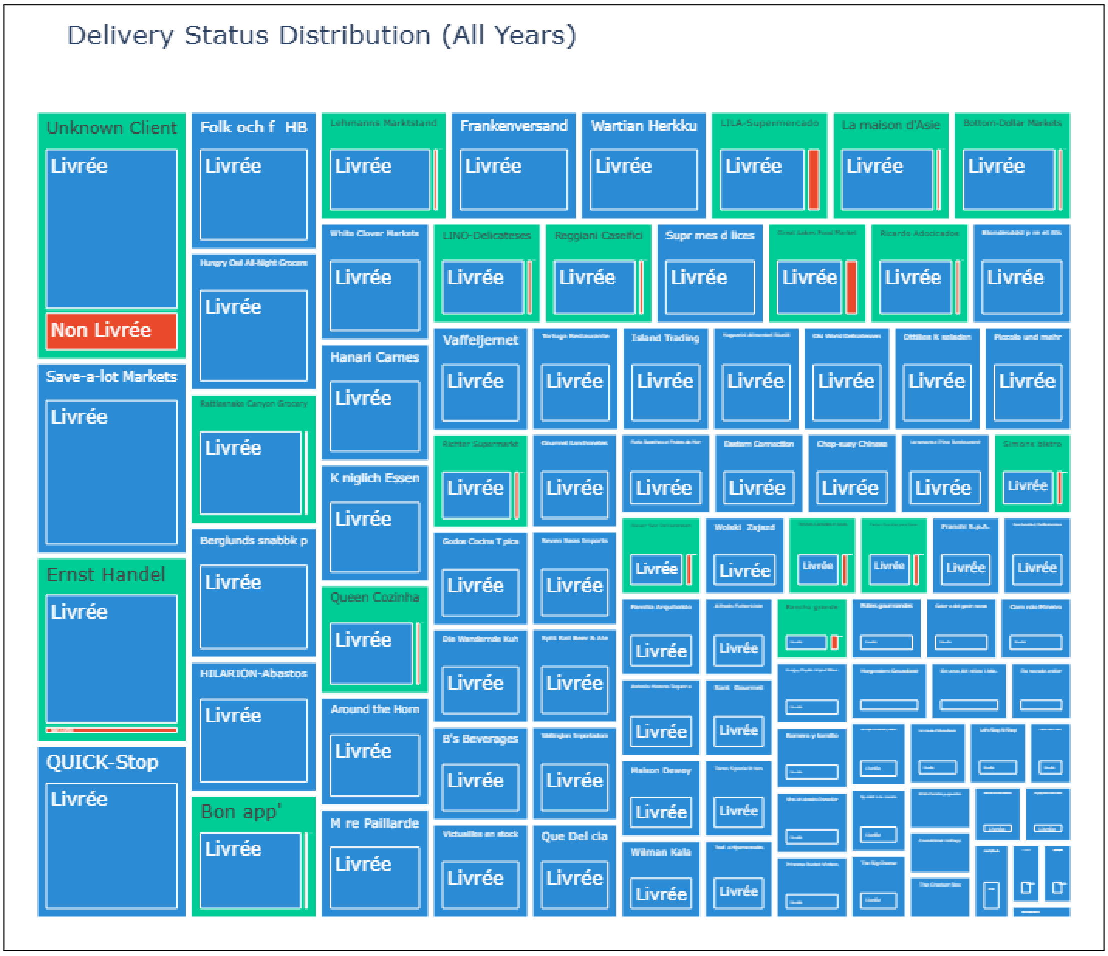

Figure 6: Client Delivery Analysis - Hierarchical treemap visualizing order distribution by company and delivery status

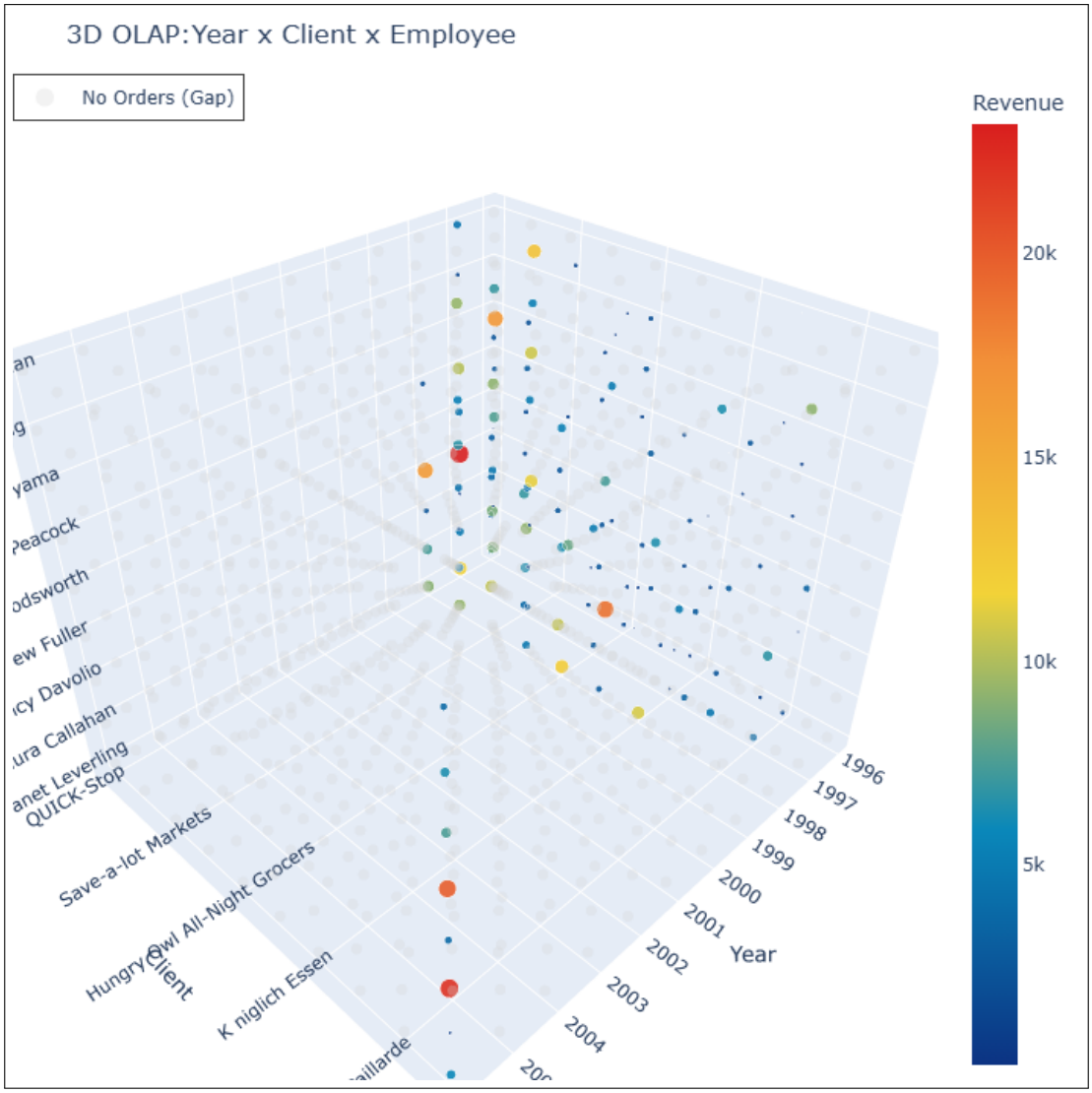

Figure 7: 3D OLAP Cube Analysis - Multi-dimensional scatter plot exploring Time × Client × Employee revenue patterns with gap markers

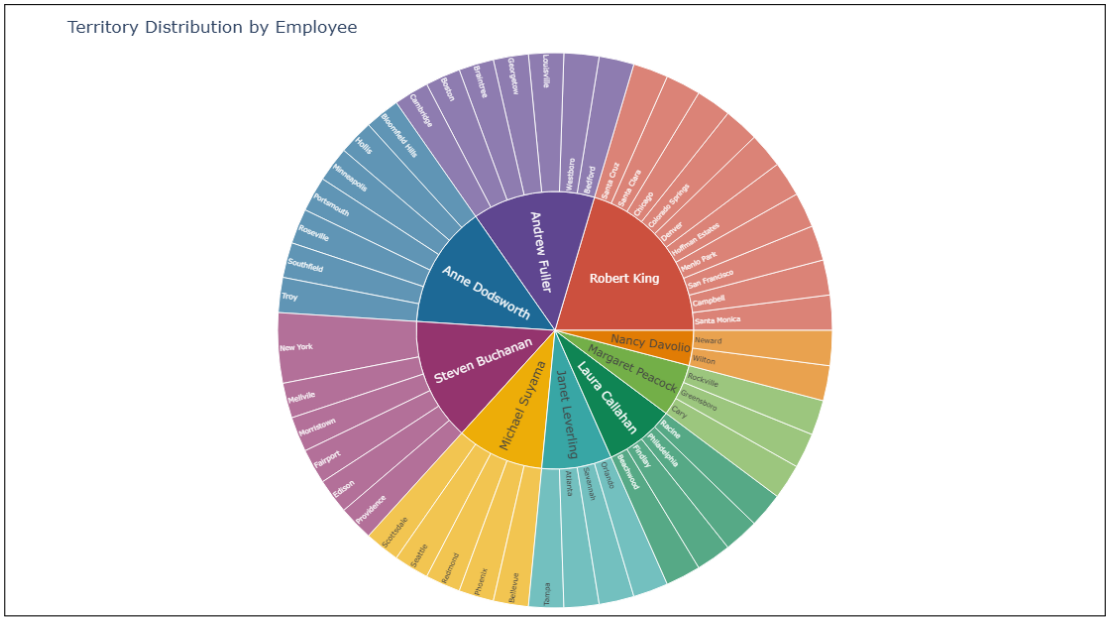

Figure 8: Territory Distribution by Employee - Sunburst diagram showing hierarchical territory assignments

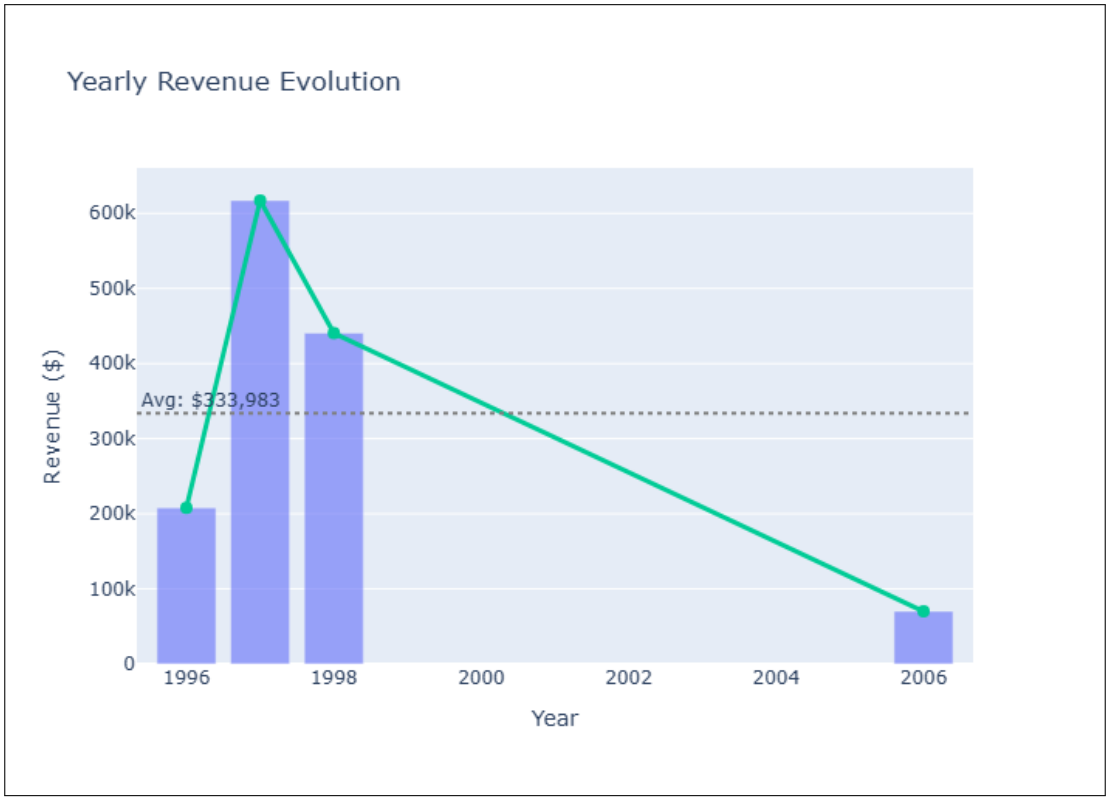

Figure 9: Revenue Evolution - Dual-layer chart combining bar values with trend line and average baseline

C.2 Figure Technical Details

Table 8: Visualization Specifications

Visualization	Chart Type	Primary Metric	Interactivity
Executive Summary	Indicator Gauges	Revenue, Orders, Delivery %	Year/Month Filter
Employee Performance	Stacked Bar	Orders by Status	Year/Month Filter
Delivery Trends	Area Chart	Order Count Over Time	Year/Month Filter
Client Analysis	Treemap	Order Distribution	Year/Month Filter
3D OLAP	3D Scatter	Revenue by 3 Dimensions	Rotation, Zoom
Territory Distribution	Sunburst	Territory Assignments	Click-to-Zoom
Revenue Evolution	Bar + Line	Period Revenue	Year/Month Filter

Note: All figures are generated using Plotly library with PNG export at 1920×1080 resolution for optimal quality.

D Appendix D: Dependencies

Listing 8: requirements.txt

```
pandas==2.0.0
numpy==1.24.0
sqlalchemy==2.0.0
pyodbc==4.0.39
matplotlib==3.7.0
plotly==5.14.0
geopandas==0.13.0
jupyter==1.0.0
seaborn==0.12.0
openpyxl==3.1.0
access-parser==0.0.2
```

E Appendix E: Project Timeline

Table 9: Development Phases

Phase	Deliverable	Duration
Requirements Analysis	Project specification	3 days
Database Setup	Northwind installation	1 day
ETL Development	extract/transform/load scripts	7 days
Data Modeling	Star schema design	2 days
Dashboard Development	Jupyter notebook	5 days
Testing & Validation	QA process	3 days
Documentation	Report & README	4 days
Total	**Complete BI Solution**	**25 days**

End of Report

Northwind Business Intelligence Solution

Engineering School ING3 - 2024/2025