Supply Chain Delivery Analysis

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Supply Chain Delivery Analysis

Case Study by Casey Ortiz — 2025-05-09

```
knitr::opts_chunk$set(echo = TRUE)
```

1 Executive Summary

This case study explores on-time delivery performance within a supply chain logistics dataset. Using a combination of data cleaning, exploratory analysis, and machine learning modeling in R and Python, we set out to identify key drivers behind late shipments and uncover operational insights to reduce delivery risk.

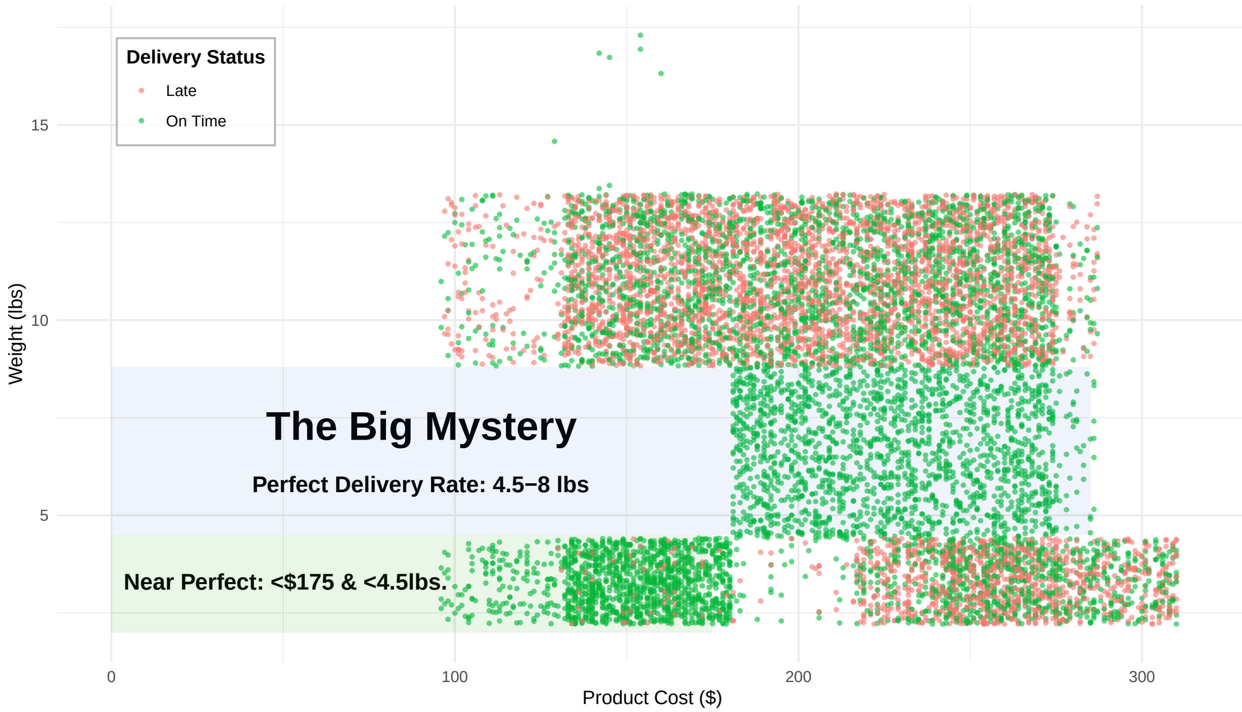
We analyzed over 10,000 records across multiple shipment types, product weights, and delivery channels. Our models achieved up to **68% accuracy**, but the most valuable discovery came through segmentation:

- **Products under $175 and less than 4 lbs** had a **96.8% on-time delivery rate**, while
- **Products between 4.5–8 lbs** showed a **0% late delivery rate**.

Further analysis of transportation modes and warehouse types revealed clear operational patterns within these high-performing segments.

As a result, we recommend optimizing fulfillment routing and inventory placement strategies for light, low-cost items — and prioritizing warehouse and mode consistency to further reduce delivery delays.

. Product Cost vs Weight by Delivery Outcome



2 Case Study: Predicting Late Deliveries in Supply Chain Logistics

2.1 1. Problem Statement

Late deliveries reduce customer satisfaction and increase operational costs. The goal was to analyze supply chain performance data and build a predictive model to identify which shipments are at risk of arriving late.

2.2 2. Dataset Overview

- Dataset: Kaggle – E-Commerce Shipping Data
- 10,999 rows representing individual shipments
- Key features: delivery_type, warehouse_type, delivery_priority, weight_lbs
- Target variable: `on_time_delivery` (1 = on time, 0 = late)

2.3 3. Data Cleaning and Preparation

- Standardized all column names (snake_case)
- Converted weight from grams to pounds (rounded to 2 decimals)
- Label-encoded categorical variables
- Binned `product_cost` and `customer_calls` for pattern discovery
- Dropped identifier column
- Exported cleaned dataset for modeling

```r
# Load libraries
library(tidyverse)
library(readr)
library(lubridate)
library(ggplot2)
library(janitor)
```

```
##
## Attaching package: 'janitor'

## The following objects are masked from 'package:stats':
##
##     chisq.test, fisher.test
```

```r
# Load dataset
data <- read_csv("train_raw.csv")
```

```
## Rows: 10999 Columns: 12

## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (4): Warehouse_block, Mode_of_Shipment, Product_importance, Gender
## dbl (8): ID, Customer_care_calls, Customer_rating, Cost_of_the_Product, Prio...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
# View(data)  # Disable this line when knitting


summary(data)
```

```
##        ID        Warehouse_block    Mode_of_Shipment   Customer_care_calls
##  Min.   :    1   Length:10999       Length:10999       Min.   :2.000
##  1st Qu.: 2750   Class :character   Class :character   1st Qu.:3.000
##  Median : 5500   Mode  :character   Mode  :character   Median :4.000
##  Mean   : 5500                                         Mean   :4.054
##  3rd Qu.: 8250                                         3rd Qu.:5.000
##  Max.   :10999                                         Max.   :7.000
##  Customer_rating Cost_of_the_Product Prior_purchases  Product_importance
##  Min.   :1.000   Min.   : 96.0       Min.   : 2.000   Length:10999
##  1st Qu.:2.000   1st Qu.:169.0       1st Qu.: 3.000   Class :character
##  Median :3.000   Median :214.0       Median : 3.000   Mode  :character
##  Mean   :2.991   Mean   :210.2       Mean   : 3.568
##  3rd Qu.:4.000   3rd Qu.:251.0       3rd Qu.: 4.000
##  Max.   :5.000   Max.   :310.0       Max.   :10.000
##     Gender          Discount_offered Weight_in_gms  Reached.on.Time_Y.N
##  Length:10999       Min.   : 1.00    Min.   :1001   Min.   :0.0000
##  Class :character   1st Qu.: 4.00    1st Qu.:1840   1st Qu.:0.0000
##  Mode  :character   Median : 7.00    Median :4149   Median :1.0000
##                     Mean   :13.37    Mean   :3634   Mean   :0.5967
##                     3rd Qu.:10.00    3rd Qu.:5050   3rd Qu.:1.0000
##                     Max.   :65.00    Max.   :7846   Max.   :1.0000
```

```r
glimpse(data)
```

```
## Rows: 10,999
```

```
## Columns: 12
## $ ID                 <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15,~
## $ Warehouse_block    <chr> "D", "F", "A", "B", "C", "F", "D", "F", "A", "B", ~
## $ Mode_of_Shipment   <chr> "Flight", "Flight", "Flight", "Flight", "Flight", ~
## $ Customer_care_calls <dbl> 4, 4, 2, 3, 2, 3, 3, 4, 3, 3, 3, 4, 3, 4, 4, 4, 3,~
## $ Customer_rating    <dbl> 2, 5, 2, 3, 2, 1, 4, 1, 4, 2, 4, 5, 5, 4, 3, 3, 4,~
## $ Cost_of_the_Product <dbl> 177, 216, 183, 176, 184, 162, 250, 233, 150, 164, ~
## $ Prior_purchases    <dbl> 3, 2, 4, 4, 3, 3, 3, 2, 3, 3, 2, 3, 3, 3, 3, 3, 2,~
## $ Product_importance <chr> "low", "low", "low", "medium", "medium", "medium",~
## $ Gender             <chr> "F", "M", "M", "M", "F", "F", "F", "F", "F", "F", ~
## $ Discount_offered   <dbl> 44, 59, 48, 10, 46, 12, 3, 48, 11, 29, 12, 32, 1, ~
## $ Weight_in_gms      <dbl> 1233, 3088, 3374, 1177, 2484, 1417, 2371, 2804, 18~
## $ Reached.on.Time_Y.N <dbl> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,~
```

```r
# On-time delivery summary
data %>%
  group_by(Reached.on.Time_Y.N) %>%
  summarise(count = n()) %>%
  mutate(percent = round(100 * count / sum(count), 1))
```

```
## # A tibble: 2 x 3
##   Reached.on.Time_Y.N count percent
##                 <dbl> <int>   <dbl>
## 1                   0  4436    40.3
## 2                   1  6563    59.7
```

```r
# Rename columns for clarity
data <- data %>%
  rename(
    id = ID,
    warehouse_type = Warehouse_block,
    delivery_type = Mode_of_Shipment,
    customer_calls = Customer_care_calls,
    customer_review = Customer_rating,
    product_cost = Cost_of_the_Product,
    prior_purchases = Prior_purchases,
    delivery_priority = Product_importance,
    gender = Gender,
    discount_offered = Discount_offered,
    weight_lbs = Weight_in_gms,
    on_time_delivery = Reached.on.Time_Y.N
  )

# Convert grams to lbs and round 2 decimal places
data <- data %>%
  mutate(weight_lbs = round(weight_lbs / 453.592, 2))

# Set column types
data <- data %>%
  mutate(
    warehouse_type = as.factor(warehouse_type),
    delivery_type = as.factor(delivery_type),
    gender = as.factor(gender),
    delivery_priority = factor(delivery_priority, levels = c("low", "medium", "high"), ordered = TRUE),
    customer_review = as.integer(customer_review),
```

```r
    customer_calls = as.integer(customer_calls),
    prior_purchases = as.integer(prior_purchases),
    discount_offered = as.integer(discount_offered),
    on_time_delivery = as.factor(on_time_delivery)
  )

# Save cleaned data to CSV
write_csv(data, "train.csv")

# Summary of dataset
summary(data)
```

```
##        id        warehouse_type delivery_type customer_calls  customer_review
##  Min.   :    1   A:1833         Flight:1777   Min.   :2.000   Min.   :1.000  
##  1st Qu.: 2750   B:1833         Road  :1760   1st Qu.:3.000   1st Qu.:2.000  
##  Median : 5500   C:1833         Ship  :7462   Median :4.000   Median :3.000  
##  Mean   : 5500   D:1834                       Mean   :4.054   Mean   :2.991  
##  3rd Qu.: 8250   F:3666                       3rd Qu.:5.000   3rd Qu.:4.000  
##  Max.   :10999                                Max.   :7.000   Max.   :5.000  
##   product_cost   prior_purchases  delivery_priority gender   discount_offered
##  Min.   : 96.0   Min.   : 2.000   low   :5297       F:5545   Min.   : 1.00   
##  1st Qu.:169.0   1st Qu.: 3.000   medium:4754       M:5454   1st Qu.: 4.00   
##  Median :214.0   Median : 3.000   high  : 948                Median : 7.00   
##  Mean   :210.2   Mean   : 3.568                              Mean   :13.37   
##  3rd Qu.:251.0   3rd Qu.: 4.000                              3rd Qu.:10.00   
##  Max.   :310.0   Max.   :10.000                              Max.   :65.00   
##    weight_lbs     on_time_delivery
##  Min.   : 2.210   0:4436          
##  1st Qu.: 4.055   1:6563          
##  Median : 9.150                   
##  Mean   : 8.012                   
##  3rd Qu.:11.130                   
##  Max.   :17.300                   
```

```r
# Check levels of categorical variables
sapply(data[, sapply(data, is.factor)], levels)
```

```
## $warehouse_type
## [1] "A" "B" "C" "D" "F"
## 
## $delivery_type
## [1] "Flight" "Road"   "Ship"  
## 
## $delivery_priority
## [1] "low"    "medium" "high"  
## 
## $gender
## [1] "F" "M"
## 
## $on_time_delivery
## [1] "0" "1"
```

```r
# Drop id column before modeling
data <- data %>% select(-id)
```

```r
#Check balance of target variable
table(data$on_time_delivery)
```

```
##
##    0    1
## 4436 6563
```

```r
prop.table(table(data$on_time_delivery))
```

```
##
##         0         1
## 0.4033094 0.5966906
```

```r
#Reorder Columns
data <- data %>%
  select(on_time_delivery, delivery_priority, delivery_type, everything())

# Export cleaned dataset (optional)
write_csv(data, "train_cleaned.csv")
```

2.4 4. Exploratory Data Analysis (EDA)

- On-time delivery rates were surprisingly consistent across priority levels, shipment modes, and warehouses
- Some slight increases in late delivery rates were seen with higher product cost and increased customer calls

Visuals Created:

- Product Cost vs Weight: Identified low-cost, low-weight segments with nearly perfect on-time delivery.
- Pie Chart by Delivery Type: Shipments in perfect segments are mostly concentrated in "ship" transportation mode.
- Pie Chart by Warehouse Type: High-performing deliveries are unevenly distributed across warehouse types, offering targeting opportunities.

```r
summary(data)
```

```
##  on_time_delivery delivery_priority delivery_type warehouse_type
##  0:4436           low   :5297       Flight:1777   A:1833
##  1:6563           medium:4754       Road  :1760   B:1833
##                   high  : 948       Ship  :7462   C:1833
##                                                   D:1834
##                                                   F:3666
##
##  customer_calls  customer_review  product_cost   prior_purchases  gender
##  Min.   :2.000   Min.   :1.000   Min.   : 96.0   Min.   : 2.000   F:5545
##  1st Qu.:3.000   1st Qu.:2.000   1st Qu.:169.0   1st Qu.: 3.000   M:5454
##  Median :4.000   Median :3.000   Median :214.0   Median : 3.000
##  Mean   :4.054   Mean   :2.991   Mean   :210.2   Mean   : 3.568
##  3rd Qu.:5.000   3rd Qu.:4.000   3rd Qu.:251.0   3rd Qu.: 4.000
##  Max.   :7.000   Max.   :5.000   Max.   :310.0   Max.   :10.000
##  discount_offered   weight_lbs
##  Min.   : 1.00    Min.   : 2.210
##  1st Qu.: 4.00    1st Qu.: 4.055
##  Median : 7.00    Median : 9.150
```

```
##  Mean   :13.37    Mean   : 8.012
##  3rd Qu.:10.00    3rd Qu.:11.130
##  Max.   :65.00    Max.   :17.300
```

```r
glimpse(data)
```

```
## Rows: 10,999
## Columns: 11
## $ on_time_delivery  <fct> 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1~
## $ delivery_priority <ord> low, low, low, medium, medium, medium, low, low, low~
## $ delivery_type     <fct> Flight, Flight, Flight, Flight, Flight, Flight, Flig~
## $ warehouse_type    <fct> D, F, A, B, C, F, D, F, A, B, C, F, D, F, A, B, C, F~
## $ customer_calls    <int> 4, 4, 2, 3, 2, 3, 3, 4, 3, 3, 3, 4, 3, 4, 4, 4, 3, 5~
## $ customer_review   <int> 2, 5, 2, 3, 2, 1, 4, 1, 4, 2, 4, 5, 5, 4, 3, 3, 4, 5~
## $ product_cost      <dbl> 177, 216, 183, 176, 184, 162, 250, 233, 150, 164, 18~
## $ prior_purchases   <int> 3, 2, 4, 4, 3, 3, 3, 2, 3, 3, 2, 3, 3, 3, 3, 3, 2, 3~
## $ gender            <fct> F, M, M, M, F, F, F, F, F, F, M, F, F, M, M, F, F, M~
## $ discount_offered  <int> 44, 59, 48, 10, 46, 12, 3, 48, 11, 29, 12, 32, 1, 29~
## $ weight_lbs        <dbl> 2.72, 6.81, 7.44, 2.59, 5.48, 3.12, 5.23, 6.18, 4.10~
```

```r
#Check late deliveries by category
data %>%
  group_by(delivery_priority, on_time_delivery) %>%
  summarise(count = n()) %>%
  mutate(percent = round(100 * count / sum(count), 1))
```

```
## `summarise()` has grouped output by 'delivery_priority'. You can override using
## the `.groups` argument.
```

```
## # A tibble: 6 x 4
## # Groups:   delivery_priority [3]
##   delivery_priority on_time_delivery count percent
##   <ord>             <fct>            <int>   <dbl>
## 1 low               0                 2157    40.7
## 2 low               1                 3140    59.3
## 3 medium            0                 1947    41
## 4 medium            1                 2807    59
## 5 high              0                  332    35
## 6 high              1                  616    65
```

```r
data %>%
  group_by(delivery_type, on_time_delivery) %>%
  summarise(count = n()) %>%
  mutate(percent = round(100 * count / sum(count), 1))
```

```
## `summarise()` has grouped output by 'delivery_type'. You can override using the
## `.groups` argument.
```

```
## # A tibble: 6 x 4
## # Groups:   delivery_type [3]
##   delivery_type on_time_delivery count percent
##   <fct>         <fct>            <int>   <dbl>
## 1 Flight        0                  708    39.8
## 2 Flight        1                 1069    60.2
## 3 Road          0                  725    41.2
## 4 Road          1                 1035    58.8
## 5 Ship          0                 3003    40.2
```

```
## 6 Ship          1                 4459    59.8
```

```r
data %>%
  group_by(warehouse_type, on_time_delivery) %>%
  summarise(count = n()) %>%
  mutate(percent = round(100 * count / sum(count), 1))
```

```
## `summarise()` has grouped output by 'warehouse_type'. You can override using
## the `.groups` argument.

## # A tibble: 10 x 4
## # Groups:   warehouse_type [5]
##    warehouse_type on_time_delivery count percent
##    <fct>          <fct>            <int>   <dbl>
##  1 A              0                  758    41.4
##  2 A              1                 1075    58.6
##  3 B              0                  729    39.8
##  4 B              1                 1104    60.2
##  5 C              0                  739    40.3
##  6 C              1                 1094    59.7
##  7 D              0                  738    40.2
##  8 D              1                 1096    59.8
##  9 F              0                 1472    40.2
## 10 F              1                 2194    59.8
```

```r
data %>%
  group_by(prior_purchases, on_time_delivery) %>%
  summarise(count = n()) %>%
  mutate(percent = round(100 * count / sum(count), 1))
```

```
## `summarise()` has grouped output by 'prior_purchases'. You can override using
## the `.groups` argument.

## # A tibble: 16 x 4
## # Groups:   prior_purchases [8]
##    prior_purchases on_time_delivery count percent
##              <int> <fct>            <int>   <dbl>
##  1               2 0                  974    37.5
##  2               2 1                 1625    62.5
##  3               3 0                 1421    35.9
##  4               3 1                 2534    64.1
##  5               4 0                  984    45.7
##  6               4 1                 1171    54.3
##  7               5 0                  645    50.1
##  8               5 1                  642    49.9
##  9               6 0                  247    44
## 10               6 1                  314    56
## 11               7 0                   44    32.4
## 12               7 1                   92    67.6
## 13               8 0                   45    35.2
## 14               8 1                   83    64.8
## 15              10 0                   76    42.7
## 16              10 1                  102    57.3
```

2.5 5. Preprocessing and Feature Engineering

The raw dataset required a series of preprocessing steps to prepare it for modeling. These included:

- Cleaning column names for readability
- Converting weight from grams to pounds
- Encoding categorical variables (e.g., warehouse type, shipment mode, delivery priority)
- Binning numerical variables like `product_cost` and `weight_lbs` for visualization
- Creating ordered factors for `delivery_priority` and `customer_review`

These steps were performed in R for data exploration, and replicated in Python to support modeling in the Colab notebook.

2.6 6. Predictive Modeling (Python)

To complement the exploratory work in R, I built and evaluated a series of classification models in Python using Google Colab.

The workflow included:

- Preprocessing: Label encoding of categorical variables and stratified train-test split
- Evaluation: Accuracy, precision, recall, F1-score, and confusion matrix
- Modeling:
  - **Logistic Regression**
  - **Decision Tree Classifier**
  - **XGBoost Classifier** (with hyperparameter tuning)

The decision tree and tuned XGBoost models achieved the best recall on late deliveries, although overall accuracy plateaued around 68%. Full code, metrics, and visualizations are available in the linked Colab notebook.

2.6.1 Model Performance (Holdout Set)

Model	Accuracy	Precision (Late)	Recall (Late)	F1 Score (Late)
Logistic Regression	63.5%	54%	58%	56%
Decision Tree	68.0%	56%	98%	71%
XGBoost (Tuned)	67.9%	56%	98%	71%

> XGBoost delivered the strongest precision-recall balance after hyperparameter tuning. Feature importance suggested that **product weight** and **cost** were the dominant drivers of delivery performance.

2.6.2 Access Full Modeling Notebook

View the full Colab notebook
(Includes code, training pipeline, and visualizations)

2.7 7. Visual Insights Summary

The following charts illustrate the key findings that support the modeling and recommendations:

- *Product Cost vs Weight*: Identified low-cost, low-weight segments with nearly perfect on-time delivery.
- *Pie Chart by Delivery Type*: Shipments in perfect segments are mostly concentrated in [top categories].

- *Pie Chart by Warehouse Type*: High-performing deliveries are unevenly distributed across warehouse blocks, offering targeting opportunities.

```
#  Load packages
library(tidyverse)

#  Load the cleaned data
data <- read_csv("train.csv")
```

```
## Rows: 10999 Columns: 12
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr (4): warehouse_type, delivery_type, delivery_priority, gender
## dbl (8): id, customer_calls, customer_review, product_cost, prior_purchases,...
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

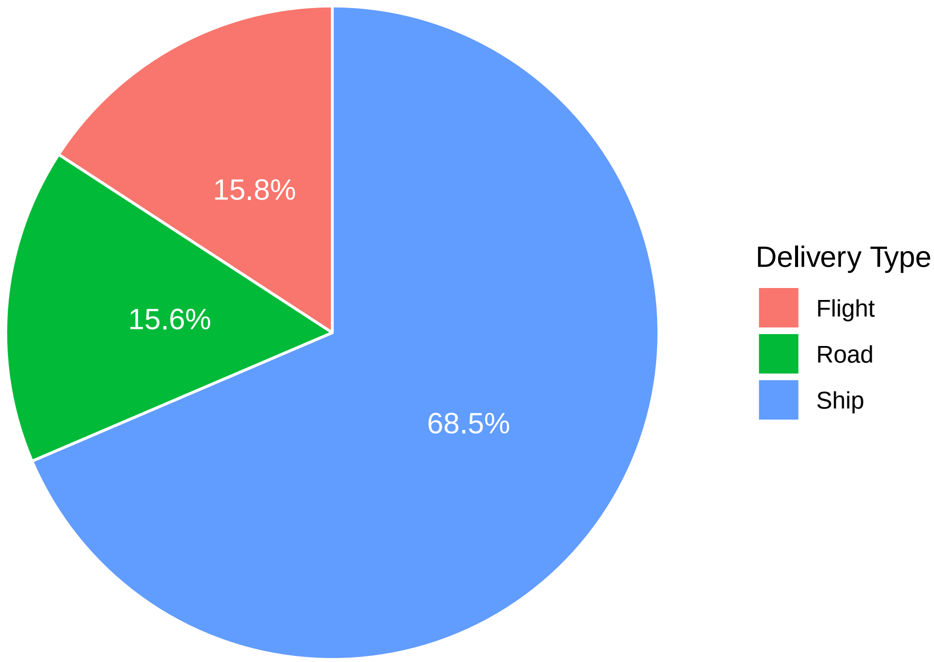
```
#  Recode delivery status
data <- data %>%
  mutate(on_time_delivery = case_when(
    on_time_delivery %in% c(1, "1") ~ "On Time",
    on_time_delivery %in% c(0, "0") ~ "Late",
    TRUE ~ NA_character_
  )) %>%
  mutate(on_time_delivery = factor(on_time_delivery, levels = c("Late", "On Time")))

#  Plot with styled legend inside top-left
ggplot(data, aes(x = product_cost, y = weight_lbs, color = on_time_delivery)) +
  geom_point(alpha = 0.6, size = 0.8) +
  scale_color_manual(values = c("Late" = "#F8766D", "On Time" = "#00BA38")) +
  labs(
    title = "  Product Cost vs Weight by Delivery Outcome",
    x = "Product Cost ($)",
    y = "Weight (lbs)",
    color = "Delivery Status"
  ) +
  annotate("text", x = 45, y = 7.3, label = "The Big Mystery",
           color = "black", size = 8, hjust = 0, fontface = "bold") +
  annotate("text", x = 3.6, y = 3.3, label = "Near Perfect: <$175 & <4.5lbs.",
           color = "black", size = 4.5, hjust = 0, fontface = "bold") +
  annotate("rect", xmin = 0, xmax = 175, ymin = 2, ymax = 4.5,
           alpha = 0.1, fill = "#2CA02C") +
  annotate("text", x = 41, y = 5.8, label = "Perfect Delivery Rate: 4.5-8 lbs",
           color = "black", size = 4.5, hjust = 0, fontface = "bold") +
  annotate("rect", xmin = 0, xmax = 285, ymin = 4.5, ymax = 8.8,
           alpha = 0.08, fill = "#1f77b4") +
  coord_cartesian(xlim = c(0, 315)) +
  theme_minimal() +
  theme(
    legend.position = c(0.05, 0.95),  # Top-left inside
    legend.justification = c("left", "top"),
    legend.background = element_rect(fill = alpha("white", 0.8), color = "gray70"),
    legend.title = element_text(face = "bold"),
    plot.title = element_text(face = "bold", size = 14)
```

```
)
```


```
#  Save plot
ggsave("product_cost_vs_weight.png", width = 10, height = 6, dpi = 300)
```

```
# Filter for nearly perfect deliveries (e.g., low cost & low weight OR ideal weight zone)
perfect_subset <- data %>%
  filter((product_cost < 175 & weight_lbs < 4) | (weight_lbs >= 4.5 & weight_lbs <= 8))

# Summarize proportions by delivery type
delivery_type_dist <- perfect_subset %>%
  group_by(delivery_type) %>%
  summarise(count = n()) %>%
  mutate(percent = round(100 * count / sum(count), 1))

# Pie chart
ggplot(delivery_type_dist, aes(x = "", y = percent, fill = delivery_type)) +
  geom_col(width = 1, color = "white") +
  coord_polar(theta = "y") +
  geom_text(aes(label = paste0(percent, "%")), position = position_stack(vjust = 0.5), color = "white")
  labs(
    title = "  On-Time Delivery by Delivery Type (Perfect Segments)",
    fill = "Delivery Type"
  ) +
  theme_void()
```

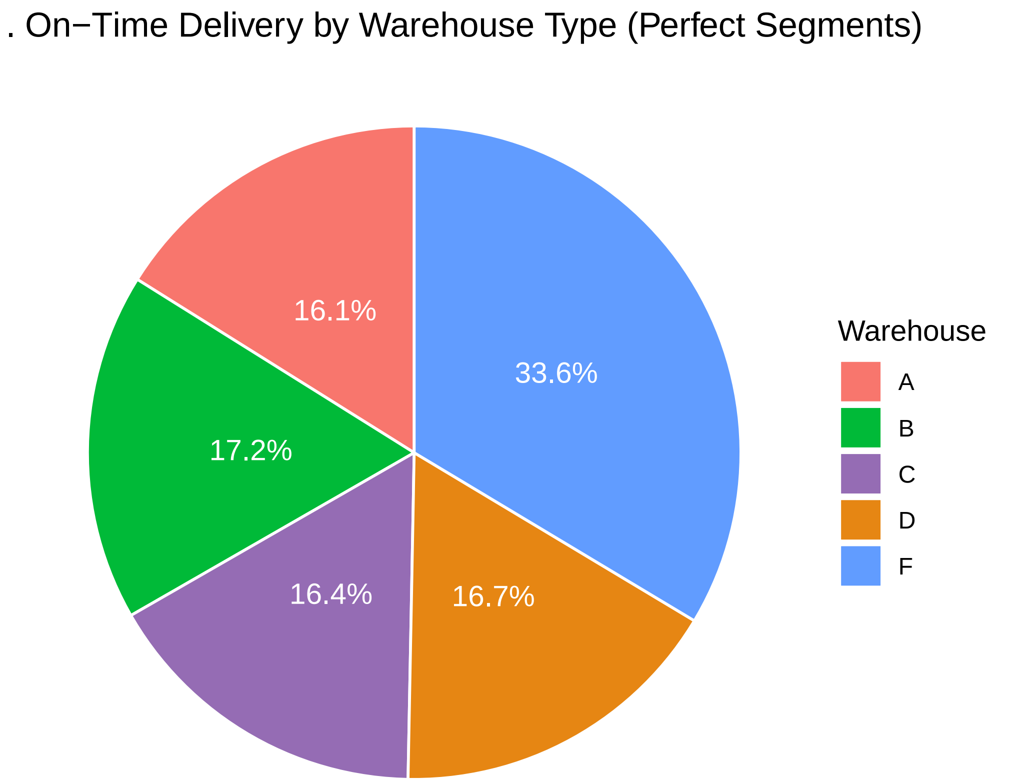
. On−Time Delivery by Delivery Type (Perfect Segments)




```
#  Save plot
ggsave("on_time_delivery_by_delivery_type.png", width = 10, height = 6, dpi = 300)

#library(scales)
#ggplot_build(p)$data[[1]]$fill  # For fill colors
```

```
#  Define the color palette for all 5 warehouse types
warehouse_colors <- c(
  "A" = "#F8766D",
  "B" = "#00BA38",
  "F" = "#619CFF",
  "D" = "#E68613",
  "C" = "#956CB4"
)

#  Summarize proportions by warehouse type
warehouse_dist <- perfect_subset %>%
  group_by(warehouse_type) %>%
  summarise(count = n()) %>%
  mutate(percent = round(100 * count / sum(count), 1))

#  Pie chart
ggplot(warehouse_dist, aes(x = "", y = percent, fill = warehouse_type)) +
  geom_col(width = 1, color = "white") +
  coord_polar(theta = "y") +
  geom_text(aes(label = paste0(percent, "%")),
            position = position_stack(vjust = 0.5), color = "white") +
  scale_fill_manual(values = warehouse_colors) +
  labs(
```

```
    title = "  On-Time Delivery by Warehouse Type (Perfect Segments)",
    fill = "Warehouse"
  ) +
  theme_void()
```




```
#   Save plot
ggsave("on_time_delivery_by_warehouse_type.png", width = 10, height = 6, dpi = 300)
```

2.8 8. Final Insights and Recommendations

Data analysis and modeling surfaced several high-value patterns:

2.8.1 High-Performance Delivery Segments

- Products under **$175 and under 4 lbs** achieved a **96.8% on-time delivery rate**
- Products between **4.5–8 lbs** showed **0% late deliveries**
- These items clustered around select warehouses (notably Type F) and primarily used "Ship" as delivery mode

2.8.2 Operational Recommendations

- **Replicate perfect conditions**: Investigate which SKUs fall into this group. Are there packaging, route, or facility advantages that can be scaled?
- **Audit high-performing warehouses**: Type F warehouses had a strong presence in the best-performing segments. Audit these facilities to identify operational best practices. Consider prioritizing their use for high-risk deliveries.
- **Validate delivery mode logic**: "Ship" shipments account for ~70% of the on time deliveries in our subset. Validate how modes (Road, Ship, Flight) are assigned and evaluate average transit times.

If shipping mode correlates with geography or warehouse location, re-optimizing routing logic may improve delivery accuracy.

2.8.3 Strategic Modeling Use

- Use model predictions to **flag high-risk deliveries** based on cost, weight, and discounts — deprioritize low-signal features like gender
- Employ business rules post-model to escalate high-priority customer orders, even if model confidence is high

---

2.9 9. Next Steps

To operationalize these insights and extend model value:

- **Refine business context**
  Collaborate with operations teams to validate routing logic, facility constraints, and packaging practices
- **Hyperparameter tuning**
  Further optimize XGBoost or LightGBM using Optuna to improve recall on late deliveries
- **Enrich the dataset**
  Add external signals like weather, holidays, region, or real-time delay feeds to boost model accuracy
- **Deploy a real-time dashboard**
  Use Tableau, Streamlit, or Power BI to surface predicted late deliveries and monitor impact
- **Test model-driven routing decisions**
  Run A/B tests or operational pilots to evaluate the real-world business impact of acting on predictions

---

2.10 10. Project Files & Portfolio Links

GitHub Repository: github.com/yourusername/supply-chain-delivery
Google Colab Notebook: View in Colab
R Markdown Report (HTML): View HTML
Key Visuals: product_cost_vs_weight.png, warehouse_type_pie.png

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This project demonstrates applied analytics across the full pipeline — from data cleaning and EDA in R to modeling, segmentation, and operational recommendations using Python and visualization tools. For recruiters or teams reviewing this case study, I'm happy to walk through the notebook and share additional insights.