Client
Hewlett Packard Inc. has been a global leader in the Printing industry for over 80 years, and their ink and toner cartridges are recognized for their high quality and cost-effectiveness. The Toner Supplies Solution Forecast department in Boise, Idaho is responsible for forecasting future demand of cartridges and ensuring inventory is efficiently managed.

Problem statement
The ratio of HP’s variation to consumption (VTC) from their toner cartridge forecasting model is inconsistent and inaccurate. Contributing variables to the forecasting model need to be analyzed and adjusted using statistical and qualitative methods to more accurately predict future demand.

Discussion
- Team looked at 3 different sheets to work with: IB-usage-share, Shipment Forecast Encoded, Tier 1-Sell Through.
- The variation in the printer data is a result of three key factors: damage, shipment, sell within country
- Team organized data and created a chart to visualize data in a more efficient manner in R.
- Switched our finding son the VTC to Python to client specifications

Results
- Our team used ARIMA modeling on R to get predicted shipments using given data for the past 2 years.
- Referring to figure 4, we noticed that the two VTC graphs of model 2SS032A seemed similar to each other, except some abnormalities in the early 2021 and late 2022.
- This gave us some insights on how our client’s shipment forecasting model is close to the data trained by ARIMA model.
- Since this model was created based on the data for a short period of time, we can create more accurate and meaningful model if we have more data from the past.

Preliminary System Model

HP’s current cartridge forecasting model

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\text{Total Expected Pages} = \text{HP's current cartridge forecasting model}
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\text{Installed Base} * \text{Monthly usage} = \text{Total Expected Pages}
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\text{Expected Cartridge Pages / Cartridge Yield = Expected Cartridges}
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\text{Shipment / Sum of Expected Cartridges = Cartridge VTC}
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Methodology

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\begin{align*}
\text{Control Chart} & \\
\text{Find where estimations are bad} & \\
\text{Show how model can be improved} & \\
\text{Show if process is stable or unstable} & \\
\text{Predict how bad estimations negatively impact model} & \\
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\begin{align*}
\text{Control limits show which values are within the desired region.} \\
\text{If any data points are outside the control limits, the variation is due to a special cause.}
\end{align*}
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\begin{align*}
\text{Figure 1. X-bar chart of both Single/Multi-function printer data sets with Python} \\
\text{Figure 2. X-bar chart of Single function printers with R} \\
\text{Figure 3. VTC of 4 types of cartridges in NA region based on the data trained using ARIMA} \\
\text{Figure 4. VTC of 2SS032A based on the existing data and trained data}
\end{align*}
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