Many companies seek to innovate and bring new products and services to market, and growth and product innovation remain top priorities for executives. CEOs have indicated their commitment to new product development growing over time (PWC 2016) and at least one survey reports new product development as their top investment priority (KPMG 2016). One common metric used to evaluate the success of a firm’s innovation efforts is the percentage of revenue derived from new products. Based on a cross-industry survey, Cooper and Edgett (2012) report that an average of 27% of a firm’s revenue comes from new products. The same survey also reports that the percentage of profit coming from new products lags the percentage of revenue coming from new products. This suggests that while new products are essential to growth, they are expensive to support.

One of the largest challenges in managing new product introductions is creating sales forecasts. Here it is important to distinguish how firms approach forecasting in general, and how the approach may differ for new product forecasting. Several studies indicate that statistical methods play a major role for sales forecasts of mature products. For example, based on a survey of 144 forecasting practitioners, Fildes and Goodwin (2007) report that 75% of all forecasts are generated or at least influenced by a statistical forecast. Contrast this with new product forecasting where market-research based methods and executive opinion dominate (Kahn 2002). While these approaches may be best, or even the only viable approach, for completely new market entries, most new products are not unlike anything we have ever seen before. Focusing just on new product forecasting, Kahn (2002) separates new products according to their “newness,” ranging from incremental cost or product-attribute improvements to “new-to-the-world” market entries. Perhaps surprisingly, even when a firm has historical data on a similar product, market research, executive opinion and sales input are still the most commonly used approaches.

Statistical forecasting for new, but not earth-redefining-new products is the focus of this paper and where we seek to make a contribution. Our objective is to develop an approach that can be effectively applied to generate forecasts for new products that are similar to previous products. Our industrial partner is Dell, and the personal computer industry, characterized by very high reliance on new product revenue and short product lifecycles, is our motivating setting. The difference in product lifecycles for computers was observed quite early, with Goldman (1982) pointing out
that computer sales were “...characterized by a short life on the market, a steep decline stage and the lack of a maturity stage.” Figure 1 shows a typical product lifecycle curve with introduction, growth, maturity and decline phases next to actual customer orders for one of the products in our data set. The simple, triangular PLC curve shown in Figure 1 fits historical orders quite well.

The central idea behind our approach is to (1) use the historical product life cycle (PLC) customer order information of previous similar products to fit a PLC curve and to (2) use the PLC curve to forecast the entire customer order evolution of ready-to-launch new products that are similar to past products. We use and compare several families of functional forms for fitting PLC curves that permit presence or absence of typical phases in the PLC such as the maturity phase.

Figure 2 summarizes our overall approach including treatment of the raw data from Dell, which required a significant amount of pre-processing. We met with a demand planner at the partner company who informed us as to the root cause of the phenomena and helped guide us as to the proper treatment of these phenomena.

We find that simple, piecewise-linear curves are effective in fitting historical PLC curves. In particular, a simple triangle performed very well on our data. The triangle has the advantage that it is easy to explain and therefore easy to implement. In addition, we found that the products in our dataset (which had a median length of 30 weeks) had almost no “mature” phase of the PLC.

We use the normalized PLC curves fit to historical data for forecasting by using time-series clustering techniques to cluster similar PLC curves and find representative curves for these clusters. A modification to our approach would be to use information provided by the company for clusters. This may work particularly well when a new product is the next version of a very similar past product.
Prepare data
- Negative order correction
- Small-volume products exclusion
- Seasonality adjustment
- Large outliers adjustment
- Promotion adjustment
- End-of-life truncation

Fit PLC curves to data
- Bass diffusion curves
- Polynomial curves (2nd – 4th degree)
- Piecewise-linear curves
  - Triangle
  - Trapezoid

Forecast using PLCs
- PLC clustering
- PLC forecasting
  - Calculate/choose PLC curve
  - Scale time and volume
  - Add seasonality

Figure 2 Forecasting using PLC curves requires several steps, including data preparation, curve fitting, and forecasting itself.

<table>
<thead>
<tr>
<th>Progress of PLC</th>
<th>Known PLC</th>
<th>Known Cluster</th>
<th>Unknown Cluster</th>
</tr>
</thead>
<tbody>
<tr>
<td>50% of PLC</td>
<td>18.7%</td>
<td>12.7%</td>
<td>2.6%</td>
</tr>
<tr>
<td>100% of PLC</td>
<td>14.0%</td>
<td>9.2%</td>
<td>3.4%</td>
</tr>
</tbody>
</table>

Table 1 Summary of percent reduction in product-wide sum of absolute error (SAE) using PLC curves compared to using the company’s forecasts. Percent reduction is measured relative to the company’s SAE in the same ‘progress within PLC’ (50% versus 100%). Even when the cluster is not known, using the product-wide ‘average’ PLC (“Unknown cluster”) improves the company’s own forecast errors by 2%-3%. Knowing the PLC of similar products or the PLC itself leads to even more improvement. SAE is summed across all the non-normalized products: naturally products with higher volumes and higher forecast errors will contribute more to these values.

For the subset of products where Dell forecasts are available, we quantify forecast accuracy improvements obtained by adopting our approach. To do this, we use lifetime quantity forecasts from Dell to scale our normalized curves, and we assume that we can use the representative curve from a product’s cluster. We note that we did not have any seasonality, promotional or cannibalization information that may have been available to Dell. Our known cluster approach resulted in absolute errors 9% lower than Dell’s historical forecasts, as measured by product-wide sum of absolute errors (SAE). This metric will measure all errors across all products, and to some extent reflects the weighted average of individual MAEs across products. We present results in Table 1 regarding percent reduction in SAE relative to the company’s value for this metric.

Effective new product forecasting is critical for many companies, and many new products fall into the category of “similar” to past products; thus, our approach would be applicable. We hope our work, and the normalized data set that we make available, stimulates new research in this area.

References