Viking case study

Hiccup Viking (HV) is the vice president of Viking Cookies that specialized into chocolate chip cookies(Choco-Chip). Viking Cookies believes that demand for cookies is seasonal and is driven by several factors such as school holidays, festivals, etc. The shelf life of Choco-chip cookies is 6 months and excess inventory and running out of stock can have financial impact. Hiccup would like to develop a forecasting model that they can use for forecasting the demand. The past monthly demand (quantity of 200 gram packets) for four years (January 2013 to December 2016) along with average price per unit during that month is shown in Table 1 below.

Table 1: Monthly demand of cookies and the average price

Period	Month	Demand in Units	Average Price	Period	Demand in Units	Average Price
1	January	10500472	37	25	10658309	36
2	February	10123572	34	26	8677622	38
3	March	7372141	36	27	7330354	37
4	April	7764303	38	28	8115471	37
5	May	6904463	40	29	8481936	34
6	June	10068862	34	30	8778999	37
7	July	6436190	40	31	10145039	32
8	August	9898436	34	32	8497839	38
9	September	6803825	39	33	8792138	34
10	October	8333787	36	34	8485358	36
11	November	7541964	39	35	8575904	36
12	December	8540662	37	36	9885156	32
13	January	10229437	37	37	11023467	35
14	February	8453201	38	38	7942451	40
15	March	7997459	35	39	12492798	32
16	April	8557825	35	40	9756258	32
17	May	7818397	36	41	8992741	32
18	June	8944499	37	42	7397807	40
19	July	8904086	36	43	9710611	32
20	August	8463682	39	44	8328379	39
21	September	7723957	37	45	11873063	32
22	October	7731422	39	46	10642507	32
23	November	8441834	35	47	10635075	32
24	December	7485122	40	48	10578547	32

Develop a forecasting model to predict demand between months 37 and 48, given the data is seasonal?

Solution: Since the demand is seasonal, the first step in forecasting is to estimate the seasonality index. We can use first 36 months data to estimate the seasonality index using method of averages. The following Table 2 gives the seasonality index for various months. For example, the seasonality index for January is 1.2251, i.e., in January the demand will increase by 22.51% from the trend.

Table2: Seasonality Index

Month	Demand(2012)	Demand(2013)	Demand(2014)	Average	SeasonalityIndex
January	10500472	10229437	10658309	10462739	1.2251
February	10123572	8453201	8677622	9084798	1.0637
March	7372141	7997459	7330354	7566651	0.8860
April	7764303	8557825	8115471	8145866	0.9538
May	6904463	7818397	8481936	7734932	0.9057
June	10068862	8944499	8778999	9264120	1.0847
July	6436190	8904086	10145039	8495105	0.9947
August	9898436	8463682	8497839	8953319	1.0483
September	6803825	7723957	8792138	7773307	0.9102
October	8333787	7731422	8485358	8183522	0.9582
November	7541964	8441834	8575904	8186567	0.9585
December	8540662	7485122	9885156	8636980	1.0113
		Average of monthly averages		**8540659**	

De-seasonalized data is calculated by dividing the value of Y_t with the corresponding seasonality index. The de-seasonalized data for periods 1 to 48 is shown below:

Period	Month	Demand in Units	Seasonality Index	De-Seasonlized Demand	Period	Demand in Units	Seasonality Index	De-Seasonlized Demand
1	January	10500472	1.225051	8571459.877	25	10658309	1.225051	8700301.087
2	February	10123572	1.063712	9517214.677	26	8677622	1.063712	8157870.706
3	March	7372141	0.885956	8321110.542	27	7330354	0.885956	8273944.563
4	April	7764303	0.953775	8140603.021	28	8115471	0.953775	8508790.517
5	May	6904463	0.90566	7623682.26	29	8481936	0.90566	9365476.361

6	June	10068862	1.084708	9282556.42	30	8778999	1.084708	8093422.427
7	July	6436190	0.994666	6470703.29	31	10145039	0.994666	10199440.54
8	August	9898436	1.048317	9442215.366	32	8497839	1.048317	8106172.125
9	September	6803825	0.910153	7475473.633	33	8792138	0.910153	9660065.596
10	October	8333787	0.958184	8697481.331	34	8485358	0.958184	8855667.032
11	November	7541964	0.95854	7868174.765	35	8575904	0.95854	8946835.525
12	December	8540662	1.011278	8445415.126	36	9885156	1.011278	9774915.107
13	January	10229437	1.225051	8350215.953	37	11023467	1.225051	8998376.939
14	February	8453201	1.063712	7946891.534	38	7942451	1.063712	7466733.207
15	March	7997459	0.885956	9026921.812	39	12492798	0.885956	14100917.65
16	April	8557825	0.953775	8972583.379	40	9756258	0.953775	10229098.91
17	May	7818397	0.90566	8632818.296	41	8992741	0.90566	9929490.538
18	June	8944499	1.084708	8245998.07	42	7397807	1.084708	6820091.571
19	July	8904086	0.994666	8951833.083	43	9710611	0.994666	9762682.976
20	August	8463682	1.048317	8073589.427	44	8328379	1.048317	7944522.565
21	September	7723957	0.910153	8486437.688	45	11873063	0.910153	13045128.2
22	October	7731422	0.958184	8068828.554	46	10642507	0.958184	11106956.05
23	November	8441834	0.95854	8806966.627	47	10635075	0.95854	11095071.36
24	December	7485122	1.011278	7401646.683	48	10578547	1.011278	10460573.3

Regression output for the de-seasonalized demand and average price using R:

Put R output here

Regression model for demand forecasting based on first 36 months of de-seasonalized data is given by

$$F_{d,t} = 20812014.673 - 335945.859 \times Average\ Price$$

Past forecast data from 37 to 48 months