Customer Lifetime Value (CLV) basics

MACHINE LEARNING FOR MARKETING IN PYTHON

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What is CLV?

- Measurement of customer value
- Can be historical or predicted
- Multiple approaches, depends on business type
- Some methods are formula-based, some are predictive and distribution based

Historical CLV

- Sum revenue of all past transactions
- Multiply by the profit margin
- Alternatively - sum profit of all past transactions, if available
- **Challenge 1** - does not account for tenure, retention and churn
- **Challenge 2** - does not account for new customers and their future revenue

$$\text{Historcal CLV} = (\text{Revenue 1} + \text{Revenue 2} + \ \ldots + \text{Revenue N}) * \text{Profit Margin}$$

Basic CLV formula

- Multiply average revenue with profit margin to get average profit
- Multiply it with average customer lifespan

$$\text{CLV} = \text{Average Revenue} * \text{Profit Margin} * \text{Average Lifespan}$$

Granular CLV formula

- Multiply average revenue per purchase with average frequency and with profit margin
- Multiply it with average customer lifespan
- Accounts for both average revenue per transaction and average frequency per period

$$\text{CLV} = (\text{Avg. revenue per purchase} * \text{Avg. Frequency} * \text{Profit Margin}) * \text{Avg. Lifespan}$$

Traditional CLV formula

- Multiply average revenue with profit margin
- Multiple average profit with the retention to churn rate
- Churn can be derived from retention and equals 1 minus retention rate
- Accounts for customer loyalty, most popular approach

$$\text{CLV} = (\text{Average Revenue} * \text{Profit Margin}) * \frac{\text{Retention Rate}}{\text{Churn Rate}}$$

Introduction to transactions dataset

- Online retail dataset
- Transactions with spent, quantity and other values

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	TotalSum	InvoiceMonth
416792	572558	22745	POPPY'S PLAYHOUSE BEDROOM	6	2011-10-25 08:26:00	2.10	14286.0	United Kingdom	12.60	2011-10
482904	577485	23196	VINTAGE LEAF MAGNETIC NOTEPAD	1	2011-11-20 11:56:00	1.45	16360.0	United Kingdom	1.45	2011-11
263743	560034	23299	FOOD COVER WITH BEADS SET 2	6	2011-07-14 13:35:00	3.75	13933.0	United Kingdom	22.50	2011-07
495549	578307	72349B	SET/6 PURPLE BUTTERFLY T-LIGHTS	1	2011-11-23 15:53:00	2.10	17290.0	United Kingdom	2.10	2011-11
204384	554656	21756	BATH BUILDING BLOCK WORD	3	2011-05-25 13:36:00	5.95	17663.0	United Kingdom	17.85	2011-05

Introduction to cohorts dataset

- Derived from online retail dataset
- Assigned acquisition month
- Pivot table with customer counts in subsequent months after acquisition
- Will use it to calculate retention rate

CohortIndex	1	2	3	4	5	6	7	8	9	10	11	12	13
AcquisitionMonth													
2010-12	716.0	246.0	221.0	251.0	245.0	285.0	249.0	236.0	240.0	265.0	254.0	348.0	172.0
2011-01	332.0	69.0	82.0	81.0	110.0	90.0	82.0	86.0	104.0	102.0	124.0	45.0	NaN
2011-02	316.0	58.0	57.0	83.0	85.0	74.0	80.0	83.0	86.0	95.0	28.0	NaN	NaN
2011-03	388.0	63.0	100.0	76.0	83.0	67.0	98.0	85.0	107.0	38.0	NaN	NaN	NaN
2011-04	255.0	49.0	52.0	49.0	47.0	52.0	56.0	59.0	17.0	NaN	NaN	NaN	NaN
2011-05	249.0	40.0	43.0	36.0	52.0	58.0	61.0	22.0	NaN	NaN	NaN	NaN	NaN
2011-06	207.0	33.0	26.0	41.0	49.0	62.0	19.0	NaN	NaN	NaN	NaN	NaN	NaN
2011-07	173.0	28.0	31.0	38.0	44.0	17.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08	139.0	30.0	28.0	35.0	14.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09	279.0	56.0	78.0	34.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10	[illegible]	67.0	30.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Calculate monthly retention

Use first month values to calculate cohort sizes

```
cohort_sizes = cohort_counts.iloc[:,0]
```

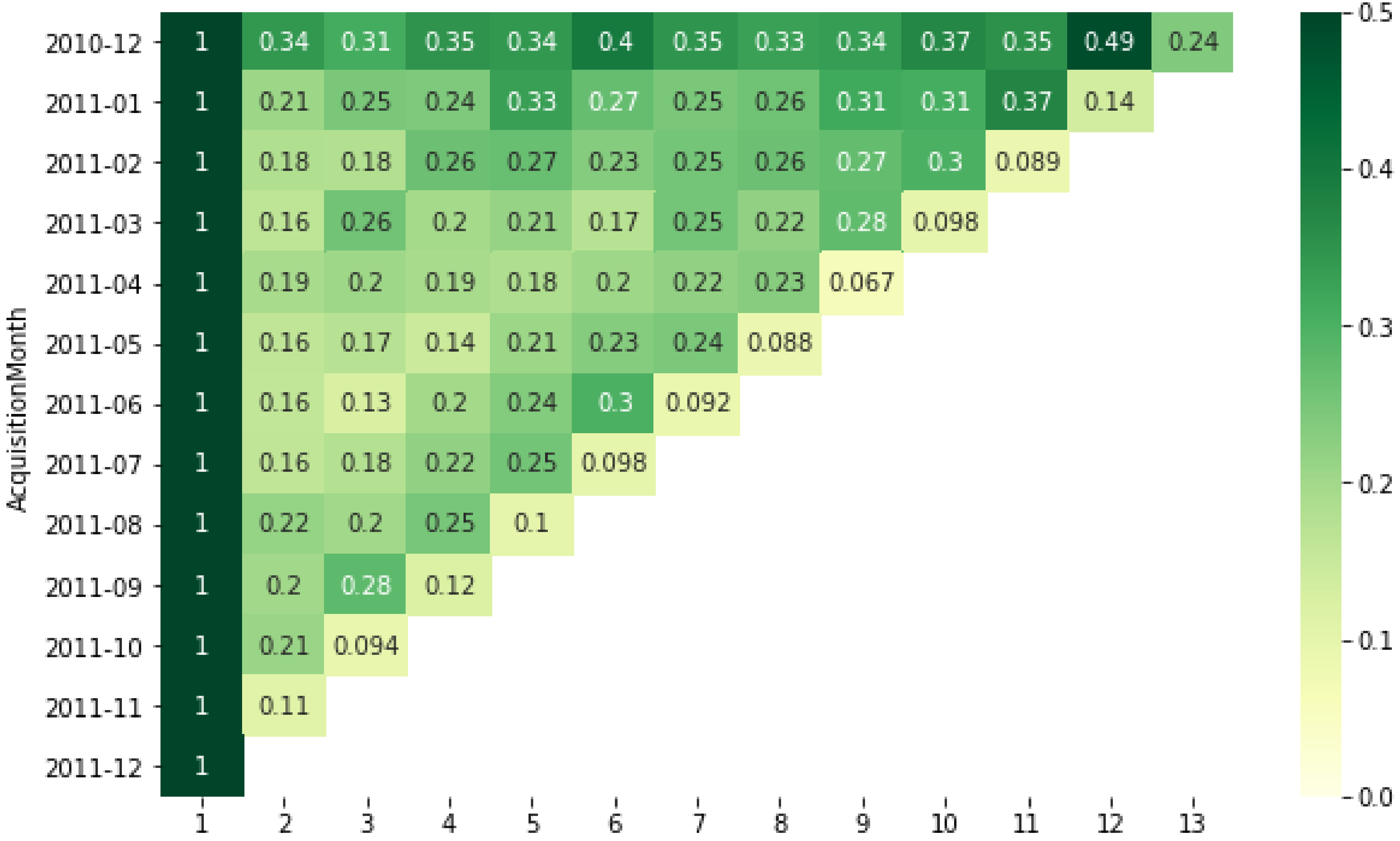
Calculate retention by dividing monthly active users by their initial sizes and derive churn values

```
retention = cohort_counts.divide(cohort_sizes, axis=0)
churn = 1 - retention
```

Plot the retention values in a heatmap

```
sns.heatmap(retention, annot=True, vmin=0, vmax=0.5, cmap="YlGn")
```

Retention table



Let's calculate some CLV metrics!

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Calculating and projecting CLV

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The goal of CLV

- Measure customer value in revenue / profit
- Benchmark customers
- Identify maximum investment into customer acquisition
- In our case - we'll skip the profit margin for simplicity and use revenue-based CLV formulas

$$\text{CLV} = \text{Average Revenue} * \frac{\text{Retention Rate}}{\text{Churn Rate}}$$

Basic CLV calculation

```
# Calculate monthly spend per customer
monthly_revenue = online.groupby(['CustomerID','InvoiceMonth'])['TotalSum'].sum().mean()
# Calculate average monthly spend
monthly_revenue = np.mean(monthly_revenue)
# Define lifespan to 36 months
lifespan_months = 36
# Calculate basic CLV
clv_basic = monthly_revenue * lifespan_months
# Print basic CLV value
print('Average basic CLV is {:.1f} USD'.format(clv_basic))
```

```
Average basic CLV is 4774.6 USD
```

Granular CLV calculation

```
# Calculate average revenue per invoice
revenue_per_purchase = online.groupby(['InvoiceNo'])['TotalSum'].mean().mean()
# Calculate average number of unique invoices per customer per month
freq = online.groupby(['CustomerID','InvoiceMonth'])['InvoiceNo'].nunique().mean()
# Define lifespan to 36 months
lifespan_months = 36
# Calculate granular CLV
clv_granular = revenue_per_purchase * freq * lifespan_months
# Print granular CLV value
print('Average granular CLV is {:.1f} USD'.format(clv_granular))
```

```
Average granular CLV is 1635.2 USD
Revenue per purchase: 34.8 USD
Frequency per month: 1.3
```

Traditional CLV calculation

```
# Calculate monthly spend per customer
monthly_revenue = online.groupby(['CustomerID','InvoiceMonth'])['TotalSum'].sum().mean()
# Calculate average monthly retention rate
retention_rate = retention_rate = retention.iloc[:,1:].mean().mean()
# Calculate average monthly churn rate
churn_rate = 1 - retention_rate
# Calculate traditional CLV
clv_traditional = monthly_revenue * (retention_rate / churn_rate)
# Print traditional CLV and the retention rate values
print('Average traditional CLV is {:.1f} USD at {:.1f} % retention_rate'.format(
                    clv_traditional, retention_rate*100))
```

```
Average traditional CLV is 49.9 USD at 27.3 % retention_rate
Monthly average revenue: 132.6 USD
```

Which method to use?

- Depends on the business model.
- Traditional CLV model - assumes churn is definitive = customer "dies".
- Traditional model is not robust at low retention values - will under-report the CLV.
- Hardest thing to predict - frequency in the future.

Let's calculate customer lifetimes values!

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Data preparation for purchase prediction

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Regression - predicting continuous variable

- Regression - type of supervised learning
- Target variable - continuous or count variable
- Simplest version - linear regression
- Count data (e.g. number of days active) sometimes better predicted by Poisson or Negative Binomial regression

Recency, frequency, monetary (RFM) features

- **RFM** - approach that underlies many feature engineering methods
- **Recency** - time since last customer transaction
- **Frequency** - number of purchases in the observed period
- **Monetary** value - total amount spent in the observed period

Explore the sales distribution by month

```
# Explore monthly distribution of observations
online.groupby(['InvoiceMonth']).size()
```

```
InvoiceMonth
2010-12    4893
2011-01    3580
2011-02    3648
2011-03    4764
2011-04    4148
2011-05    5018
2011-06    4669
2011-07    4610
2011-08    4744
2011-09    7189
2011-10    8808
2011-11    9513
dtype: int64
```

Separate feature data

```
# Exclude target variable
online_X = online[online['InvoiceMonth']!='2011-11']

# Define snapshot date
NOW = dt.datetime(2011,11,1)

# Build the features
features = online_X.groupby('CustomerID').agg({
                                'InvoiceDate': lambda x: (NOW - x.max()).days,
                                'InvoiceNo': pd.Series.nunique,
                                'TotalSum': np.sum,
                                'Quantity': ['mean', 'sum']
                                }).reset_index()

features.columns = ['CustomerID', 'recency', 'frequency',
                    'monetary', 'quantity_avg', 'quantity_total']
```

Review features

```
print(features.head())
```

	CustomerID	recency	frequency	monetary	quantity_avg	quantity_total
0	12747.0	27	9	643.33	10.523810	221
1	12748.0	5	107	4576.23	6.727110	3747
2	12749.0	91	2	598.65	8.791667	211
3	12820.0	5	3	202.62	10.307692	134
4	12822.0	31	2	146.15	9.666667	87

Calculate target variable

```
# Build pivot table with monthly transactions per customer
cust_month_tx = pd.pivot_table(data=online, index=['CustomerID'],
                               values='InvoiceNo',
                               columns=['InvoiceMonth'],
                               aggfunc=pd.Series.nunique, fill_value=0)
print(cust_month_tx.head())
```

InvoiceMonth	2010-12	2011-01	2011-02	2011-03	2011-04	2011-05	2011-06	2011-07	2011-08	2011-09	2011-10	2011-11
CustomerID												
12747.0	2	1	0	1	0	2	1	0	1	0	1	1
12748.0	24	2	4	9	3	17	12	8	9	9	10	41
12749.0	0	0	0	0	0	1	0	0	1	0	0	1
12820.0	0	1	0	0	0	0	0	0	0	1	1	0
12822.0	0	0	0	0	0	0	0	0	0	2	0	0

Finalize data preparation and split to train/test

```
# Store identifier and target variable column names
custid = ['CustomerID']
target = ['2011-11']

# Extract target variable
Y = cust_month_tx[target]

# Extract feature column names
cols = [col for col in features.columns if col not in custid]

# Store features
X = features[cols]
```

Split data to training and testing

```
# Randomly split 25% of the data to testing
from sklearn.model_selection import train_test_split
train_X, test_X, train_Y, test_Y = train_test_split(X, Y,
                                                    test_size=0.25,
                                                    random_state=99)

# Print shapes of the datasets
print(train_X.shape, train_Y.shape, test_X.shape, test_Y.shape)
```

```
(2529, 5) (2529, 1) (843, 5) (843, 1)
```

Let's work on data preparation exercises!

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Predicting customer transactions

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Modeling approach

- Linear regression to predict next month's transactions.
- Same modeling steps as with logistic regression.

Modeling steps

1. **Split** data to training and testing
2. **Initialize** the model
3. **Fit** the model on the training data
4. **Predict** values on the testing data
5. **Measure** model performance on testing data

Regression performance metrics

Key metrics:

- **Root mean squared error (RMSE)** - Square root of the average squared difference between prediction and actuals
- **Mean absolute error (MAE)** - Average absolute difference between prediction and actuals
- **Mean absolute percentage error (MAPE)** - Average percentage difference between prediction and actuals (actuals can't be zeros)

Additional regression and supervised learning metrics

- **R-squared** - statistical measure that represents the percentage proportion of variance that is explained by the model. Only applicable to regression, **not** classification. **Higher is better.**
- Coefficient **p-values** - probability that the regression (or classification) coefficient is observed due to chance. **Lower is better.** Typical thresholds are 5% and 10%.

Fitting the model

```
# Import the linear regression module
from sklearn.linear_model import LinearRegression

# Initialize the regression instance
linreg = LinearRegression()

# Fit model on the training data
linreg.fit(train_X, train_Y)

# Predict values on both training and testing data
train_pred_Y = linreg.predict(train_X)
test_pred_Y = linreg.predict(test_X)
```

Measuring model performance

```python
# Import performance measurement functions
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
# Calculate metrics for training data
rmse_train = np.sqrt(mean_squared_error(train_Y, train_pred_Y))
mae_train = mean_absolute_error(train_Y, train_pred_Y)
# Calculate metrics for testing data
rmse_test = np.sqrt(mean_squared_error(test_Y, test_pred_Y))
mae_test = mean_absolute_error(test_Y, test_pred_Y)
# Print performance metrics
print('RMSE train: {:.3f}; RMSE test: {:.3f}\nMAE train: {:.3f}, MAE test: {:.3f}'.format(
                            rmse_train, rmse_test, mae_train, mae_test))
```

```
RMSE train: 0.717; RMSE test: 1.216
MAE train: 0.514, MAE test: 0.555
```

Interpreting coefficients

- Need to assess statistical significance
- Introduction to `statsmodels` library
- Gives in-depth model summary

Build regression model with statsmodels

```python
# Import the library
import statsmodels.api as sm

# Convert target variable to `numpy` array
train_Y = np.array(train_Y)

# Initialize and fit the model
olsreg = sm.OLS(train_Y, train_X)
olsreg = olsreg.fit()

# Print model summary
print(olsreg.summary())
```

Regression summary table

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.488
Model:                            OLS   Adj. R-squared:                  0.487
Method:                 Least Squares   F-statistic:                     480.3
Date:                Sun, 18 Aug 2019   Prob (F-statistic):               0.00
Time:                        17:03:53   Log-Likelihood:                -2769.8
No. Observations:                2529   AIC:                             5550.
Df Residuals:                    2524   BIC:                             5579.
Df Model:                           5
Covariance Type:            nonrobust
==================================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
----------------------------------------------------------------------------------
recency            0.0002      0.000      1.701      0.089   -2.92e-05       0.000
frequency          0.1316      0.003     38.000      0.000       0.125       0.138
monetary        1.001e-06   3.59e-05      0.028      0.978   -6.95e-05    7.15e-05
quantity_avg       0.0001      0.000      0.803      0.422      -0.000       0.000
quantity_total    -0.0001   5.74e-05     -2.562      0.010      -0.000   -3.45e-05
==============================================================================
```

Interpreting R-squared

```
                            OLS Regression Results
==============================================================================
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Model:                            OLS   Adj. R-squared:                  0.487
Method:                 Least Squares   F-statistic:                     480.3
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quantity_total    -0.0001   5.74e-05     -2.562      0.010      -0.000   -3.45e-05
==============================================================================
```

Interpreting coefficient p-values

```
                            OLS Regression Results
==============================================================================
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Model:                            OLS   Adj. R-squared:                  0.487
Method:                 Least Squares   F-statistic:                     480.3
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==============================================================================
```

Let's build some regression models!

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