## Exponential Moving Average (EMA)

The exponential moving average (EMA) is a variant of moving averages that looks and acts like any other moving average. If you look at a chart with a simple moving average (SMA) and an exponential moving average, you won’t be able to differentiate at first glance. However, under the hood, there are key differences regarding how the SMA and EMA are calculated.

Let’s say you are trading the daily chart and looking at last month’s [price action](http://tradingsim.com/blog/price-action-trading-strategies/). Would you agree that analyzing last week’s price action would offer a better understanding of how the market is behaving today, and today’s price action would likely dictate tomorrow’s price action?

Since recent price data plays a more relevant compared to older price data in shaping the market, it is common sense that you should give more weight to recent data.

The exponential moving average (EMA) applies this very notion that traders should pay more attention to the recent price action compared to the old ones. Although most modern charting packages automatically calculates and plots the various types of moving averages on a price chart, it is always  a good idea that you know how they are calculated as it helps to increase your understanding regarding why moving averages behave differently.

### How to calculate the EMA

Basically, you need to go through three steps to calculate the exponential moving average for trading any instrument.

First, we need to figure out the simple moving average (SMA). If we want to calculate the SMA of the last 10 [days](http://tradingsim.com/blog/trading-days-in-a-year/), we simply sum up the values of the last 10 closing prices and divide it by 10 to get the SMA.

Once we have the SMA, next we need to figure out the weighting multiplier for the number of periods we want to calculate for the EMA.

The weighting multiplier is calculated with the following formula:

EMA(current) = ( (Price(current) – EMA(prev) ) x Multiplier) + EMA(prev)

You should always remember that the number of periods will have a profound effect on the weighting multiplier as it places greater importance to the most recent price action.

As we are using 10 days in this exponential moving average example, the weighting multiplier would be calculated like this:

(2 / (Time periods + 1) ) = (2 / (10 + 1) ) = 0.1818 (18.18%)

Finally, once you have calculated the SMA and  weighting multiplier values, you can easily calculate the EMA with the following calculation:

(Closing price - EMA(previous day)) x multiplier + EMA(previous day)

Granville’s Strategy

Once we calculate the EMA, we can make a trading decision by using Granville’s strategy.

(1)If the 200 day average line flattens out following a previous decline, or is advancing, and the price of the stock penetrates that average line on the upside, this comprises a major buying signal.

(2) If the price of the stock falls below the 200 day moving average price line while the average line is still rising, this also is considered to be a buying opportunity.

(3)If the stock price is above the advancing 200-day line and is declining toward that line, fails to go through and starts to turn up again, this is a buying signal.

(4) If the stock price falls too fast under the declining 200-day average line, it is entitled to an advance back toward the average line and the stock can be bought for this short-term technical rise.

(5) If the 200-day average line flattens out following a previous rise, or is declining, and the price of the stock penetrates that line on the downside, this comprises a major selling signal.

(6) If the price of the stock rises above the 200 day moving average price line while the average line is still falling, this also is considered to be a selling opportunity.

(7) If the stock price is below the falling 200-day line, and is advancing toward that line, fails to go through and starts to turn down again, this is a selling signal.

1. If the stock price advances too fast above the advancing 200 day average line, it is entitled to a reaction back toward the average line and the stock can be sold for this short-term technical reaction.

## Relative Strength Index (RSI)

Developed J. Welles Wilder, the Relative Strength Index (RSI) is a momentum oscillator that measures the speed and change of price movements. RSI oscillates between zero and 100. Traditionally, and according to Wilder, RSI is considered overbought when above 70 and oversold when below 30. Signals can also be generated by looking for divergences, failure swings and centerline crossovers. RSI can also be used to identify the general trend.

RSI is an extremely popular [momentum indicator](http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators:introduction_to_technical_indicators_and_oscillators" \o "http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators:introduction_to_technical_indicators_and_oscillators) that has been featured in a number of articles, interviews and books over the years. In particular, Constance Brown's book, Technical Analysis for the Trading Professional, features the concept of bull market and bear market ranges for RSI. Andrew Cardwell, Brown's RSI mentor, introduced positive and negative reversals for RSI. In addition, Cardwell turned the notion of divergence, literally and figuratively, on its head.

The calculation formation is:



RSI is a versatile momentum oscillator that has stood the test of time. Despite changes in [volatility](http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators:standard_deviation_volatility" \o "chart_school:technical_indicators:standard_deviation_volatility) and the markets over the years, RSI remains as relevant now as it was in Wilder's days. While Wilder's original interpretations are useful to understanding the indicator, the work of Brown and Cardwell takes RSI interpretation to a new level. Adjusting to this level takes some rethinking on the part of the traditionally schooled chartists. Wilder considers overbought conditions ripe for a reversal, but overbought can also be a sign of strength. Bearish divergences still produce some good sell signals, but chartists must be careful in strong trends when bearish divergences are actually normal. Even though the concept of positive and negative reversals may seem to undermine Wilder's interpretation, the logic makes sense and Wilder would hardly dismiss the value of putting more emphasis on price action. Positive and negative reversals put price action of the underlying security first and the indicator second, which is the way it should be. Bearish and bullish divergences place the indicator first and price action second. By putting more emphasis on price action, the concept of positive and negative reversals challenges our thinking towards momentum oscillators.

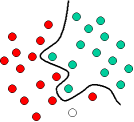
## Support Vector Machine - Regression (SVR)

In [machine learning](https://en.wikipedia.org/wiki/Machine_learning" \o "Machine learning), support vector machines (SVMs, also support vector networks[[1]](https://en.wikipedia.org/wiki/Support_vector_machine" \l "cite_note-CorinnaCortes-1)) are [supervised learning](https://en.wikipedia.org/wiki/Supervised_learning" \o "Supervised learning) models with associated learning [algorithms](https://en.wikipedia.org/wiki/Algorithm" \o "Algorithm) that analyze data used for [classification](https://en.wikipedia.org/wiki/Statistical_classification" \o "Statistical classification) and [regression analysis](https://en.wikipedia.org/wiki/Regression_analysis" \o "Regression analysis). Given a set of training examples, each marked for belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other, making it a non-[probabilistic](https://en.wikipedia.org/wiki/Probabilistic_classification" \o "Probabilistic classification) [binary](https://en.wikipedia.org/wiki/Binary_classifier" \o "Binary classifier) [linear classifier](https://en.wikipedia.org/wiki/Linear_classifier" \o "Linear classifier). An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

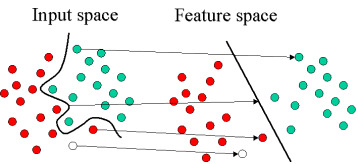
Support Vector Machines are based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships. A schematic example is shown in the illustration below. In this example, the objects belong either to class GREEN or RED. The separating line defines a boundary on the right side of which all objects are GREEN and to the left of which all objects are RED. Any new object (white circle) falling to the right is labeled, i.e., classified, as GREEN (or classified as RED should it fall to the left of the separating line).



The above is a classic example of a linear classifier, i.e., a classifier that separates a set of objects into their respective groups (GREEN and RED in this case) with a line. Most classification tasks, however, are not that simple, and often more complex structures are needed in order to make an optimal separation, i.e., correctly classify new objects (test cases) on the basis of the examples that are available (train cases). This situation is depicted in the illustration below. Compared to the previous schematic, it is clear that a full separation of the GREEN and RED objects would require a curve (which is more complex than a line). Classification tasks based on drawing separating lines to distinguish between objects of different class memberships are known as hyperplane classifiers. Support Vector Machines are particularly suited to handle such tasks.



he illustration below shows the basic idea behind Support Vector Machines. Here we see the original objects (left side of the schematic) mapped, i.e., rearranged, using a set of mathematical functions, known as kernels. The process of rearranging the objects is known as mapping (transformation). Note that in this new setting, the mapped objects (right side of the schematic) is linearly separable and, thus, instead of constructing the complex curve (left schematic), all we have to do is to find an optimal line that can separate the GREEN and the RED objects.



Support Vector Machine can also be used as a regression method, maintaining all the main features that characterize the algorithm (maximal margin). The Support Vector Regression (SVR) uses the same principles as the SVM for classification, with only a few minor differences. First of all, because output is a real number it becomes very difficult to predict the information at hand, which has infinite possibilities. In the case of regression, a margin of tolerance (epsilon) is set in approximation to the SVM which would have already requested from the problem. But besides this fact, there is also a more complicated reason, the algorithm is more complicated therefore to be taken in consideration. However, the main idea is always the same: to minimize error, individualizing the hyper plane which maximizes the margin, keeping in mind that part of the error is tolerated.