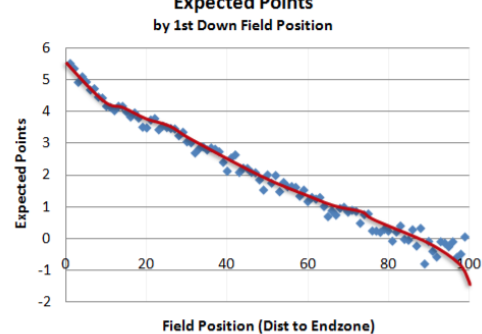
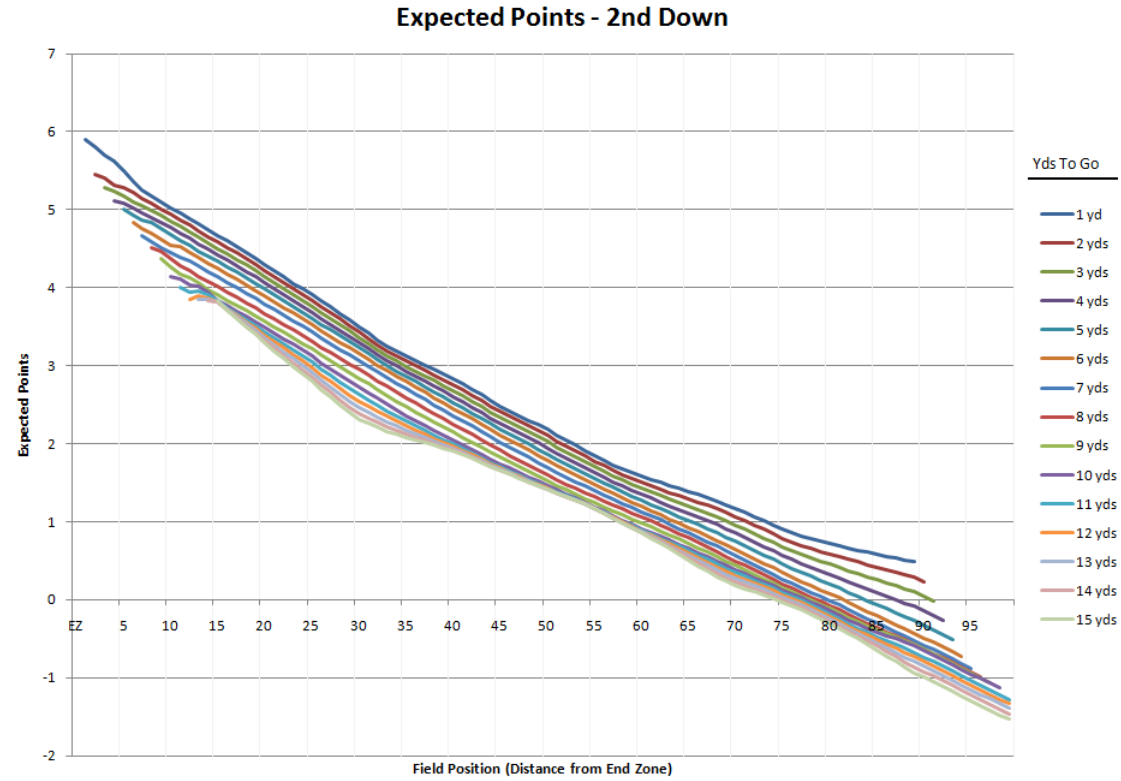
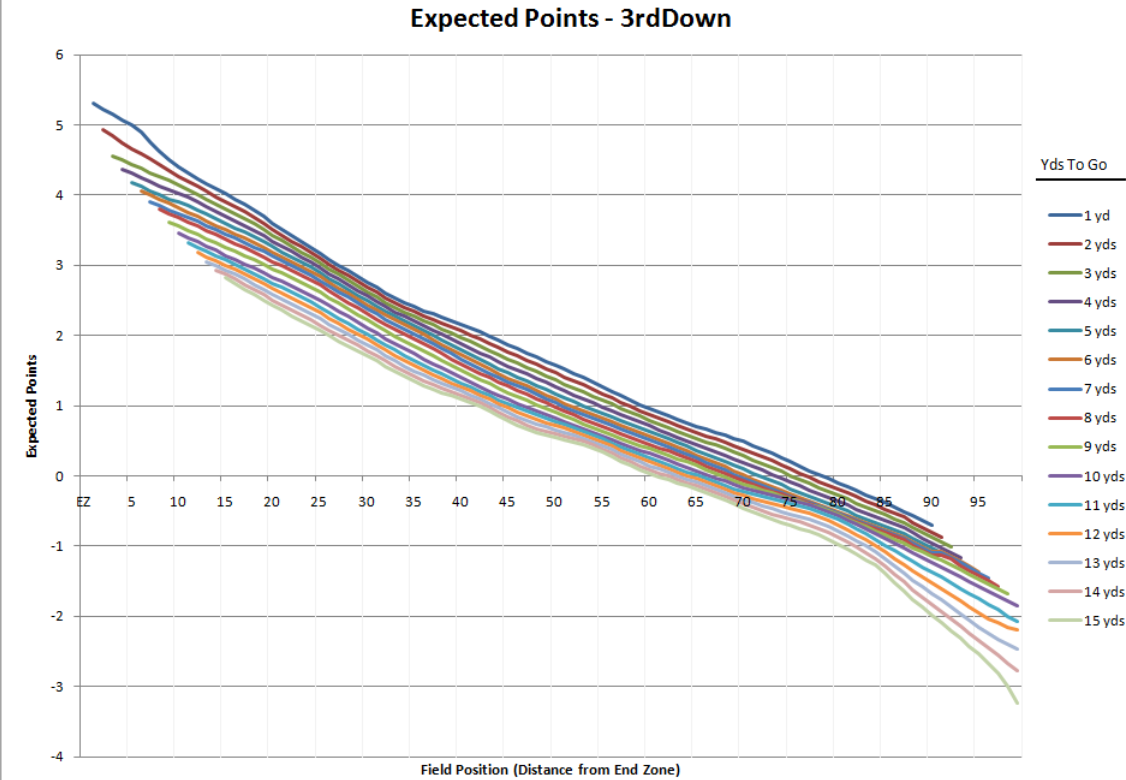
Expected Points and Expected Points Added Explained: Brian Burke

* Football = sport of strategy + decision making.
* But comparing potential risks + rewards of various options, need to be able to **properly measure value of possible outcomes**
* **Value of a football play** has traditionally been measured in **yards gained** 🡺 FLAWED measure b/c ***not all yards are equal*** (4-yd. gain on 3rd + 3 = much more valuable than 4­ yards on 3rd + 8)
* Any measure of success must consider the “down and distance” situation.
* **Field position** = also an important consideration 🡺 Yards near goal line = tougher + more valuable at midfield + yards lost near one’s own goal line = more costly as well.
* Can measure values of situations +, by extension, the outcomes of plays by establishing an **equivalence** in terms of points.
* Start by looking back through recent NFL history at the ‘**next points scored’** for all plays
* Ex: Look @ all 1st + 10s from an offense’ own 20­-yard line 🡪 team on offense will score next slightly more often than opponent.
* If we add up all ‘next points’ scored for + against offense’s team, whether on current or subsequent drives, can estimate **net point advantage** an offense can expect for any football situation
* For a 1st + 10 @ own 20, it’s **+0.4 net points**, + at opponent’s 20, it’s **+4.0 net points**.
* These net point values = called **Expected Points (EP),** + every down­-distance­-field position situation has a corresponding EP value.
* Suppose offense has a 1st + 10 @ midfield 🡪 worth +2.0 EP.
* 5­-yard gain sets up 2nd + 5 from the 45 🡪 +2.1 EP.
* Therefore, *that* 5-­yard gain *in that particular situation* = a **+0.1 gain in EP**, where gain = called **Expected Points Added (EPA).**
* Likewise, a 5-­yard loss on 1st @ midfield creates 2nd + 15 from own 45 = worth +1.2 EP representing a net difference of -­0.8 EPA.
* Can value turnovers in same way.
* Suppose on 2nd + 5 @ opponent’s 45 🡪 fumble recovered by defense
* 2nd + 5 was worth +2.2 EP, but now opponent has 1st + 10 on own 45, worth +2.1 EP *to them*.
* Result of the play = **­2.1 EP** for original offense for a **net loss of ­4.3 EP**.
* On average, a fumble in that situation means net expected loss of a little more than 4 points.
* **To be of good use for most kinds of analysis, need the measure of success to be linear**.
* In this case, it means +2 EP = exactly twice as good as +1 EP, +4 EP = twice as good as +2 EP, etc.
* **Need linearity when analyzing decisions**.
* What would we rather have: 100% chance of +3 EP, or 60% chance at +6 EP w/ 40% chance of 0 EP?
* To answer this question definitively, each net point of advantage must be equally valuable to a team
* Problem 🡺 We all know being up by 1 @ the end of a game = just as good as being up by 50, so **not all points are equally valuable**.
* Teams well ahead sacrifice point advantages in exchange for running time off the clock, which helps them win.
* **To mitigate that problem, baseline EP values for each down-­distance-­field position situation must be created based on real game situations when points = equally valuable + time is not yet a factor**.
* Baseline EP values = therefore based *only on game situations when score was w/in 10 points in Q1 or Q3.*
* This eliminates situations like ‘trash time,’ + other distortions.
* EP + EPA have a variety of applications
* Can use EP to measure + compare relative value of runs vs. passes in various situations.
* Can tally up EPA for individual players + for teams for a more accurate valuation than from traditional stats
* Perhaps most useful application of EP = analysis of 4th down decisions, which suggests teams should be going for it far more often.
* Example of what EP values look like on 1st down:



* Expected Points on 1st downs = easy to compute b/c there’re so many 1st + 10s compared to any other down-distance combo
* For 2nd + 3rd downs, not nearly as simple as averaging next scores for each field position
* There’s considerable noise (or sample error) b/c there’re relatively few cases of each down-distance combo.
* To get reasonable estimates for later down situations, use a smoothing technique [**LOESS**](http://en.wikipedia.org/wiki/Local_regression) = fancy way of drawing a crayon through a collection of noisy data points
* Challenge = to get estimates consistent across 3 dimensions: field position, down, distance to goal



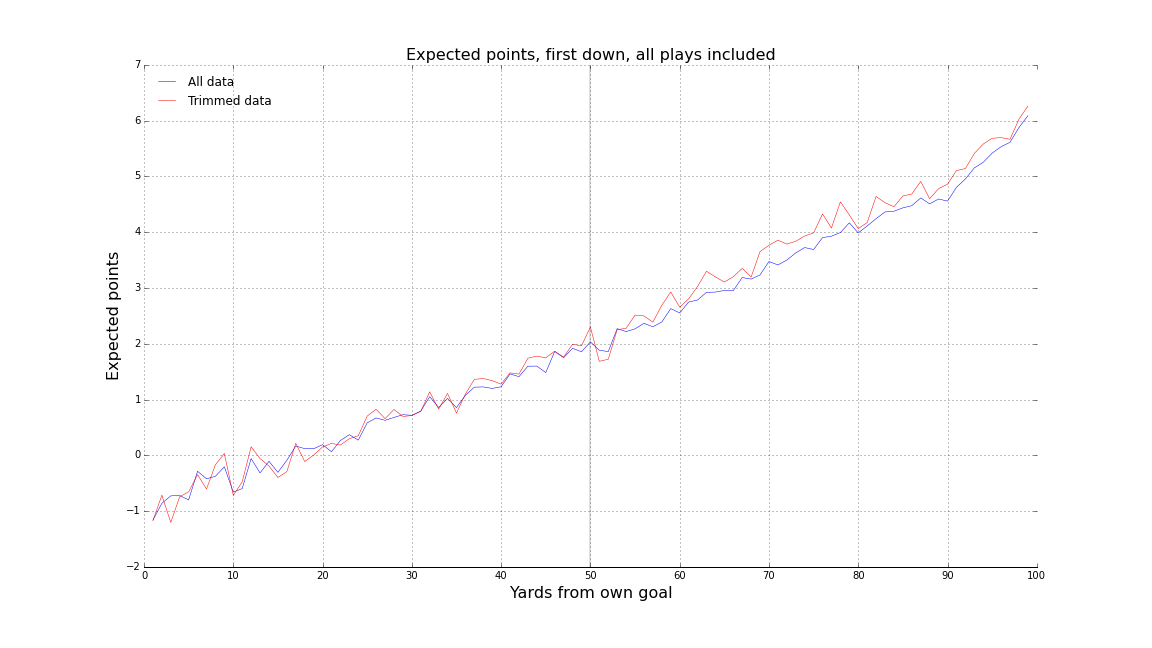


Expected Points Part 1: Building a Model and Estimating Uncertainty

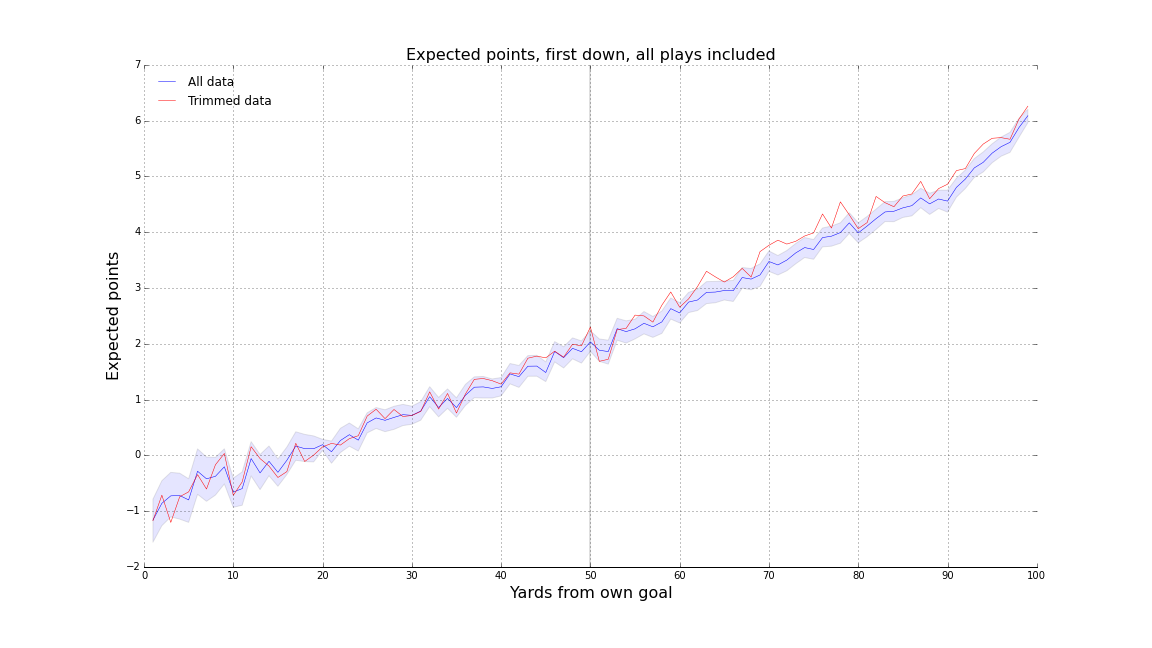
* **Expected points** got renewed attention from [FiveThirtyEight article](http://fivethirtyeight.com/features/kickers-are-forever/) on rise of kicking accuracy over time + how 4th-down decision-making could be affected.
* However, lots of EP models already exist
* 2 YouTube tutorials ([1](https://www.youtube.com/watch?v=JclgcQgPOcE), [2](https://www.youtube.com/watch?v=IDLCulWNGyk)) on building an expected points model
* Basic idea behind EP:
* **Given any combo of down, yards to go, + distance from end zone, the expected value of the points from that position = the average of every *next score* from that position.**
* Next score could be on that play via a FG or TD, could be several-to-many plays later through a successful drive.
* Could also be negative 🡪 next points scored by other team.
* Can imagine EP from one's own 1-yard line = probably negative, b/c even if you punt the ball away, opponent will probably have very good field position to start next drive + will likely get at least a FG
* Similarly, can imagine expected points on 1st + goal from opponent's 1 = somewhere between 3 + 7 b/c you'll have nearly 4 tries (barring turnovers) to score a TD or FG
* Reason to build these kinds of models = **to place a value on every position on the field to allow for in-game decision-making.**
* By being able to compare EP from a variety of possible outcomes, can choose play call that allows for maximizing # of EP
* May be game scenarios when more interested in maximizing EP (early, when an individual play may not have much impact on overall win probability)
* Building the model itself w/ Python = easier w/ indexing + grouping capabilities of [pandas](http://pandas.pydata.org/) 🡪 data manipulation + taking the mean.
* all of the code in an IPython notebook on [Github](http://github.com/treycausey/thespread/tree/master/notebooks/expected_points.ipynb) ([NBViewer](http://nbviewer.ipython.org/github/treycausey/thespread/blob/master/notebooks/expected_points.ipynb))

**Exploring the assumptions**

* # of assumptions that go into building this kind of model.
* 1) Throw out plays where score difference > 10 + those from 2nd + 4th quarters b/c teams operate differently when facing/delivering a blowout or when half is about to end.
* winning team may just run RB repeatedly towards end of game, not really trying to gain yards or score more, which could distort effects of these plays on points scored.
* Can presenting how assumptions change analyses = 1 way of measuring effects of assumptions, but also a good way to see how **robust** your conclusions are to changes in the data.
* EP as a function of field position on 1st down w/ + w/out these plays removed.



* Surprisingly, not much of a difference 🡺 trimmed data produces slightly higher estimates of EP than complete data in the opponent's half of the field.
* But *how much* of a difference is "not much"?
* Can use a local regression **smoother** **LOESS** to remove bumps + get better sense of 'true' EP contained in those noise lines.
* Can also use [**bootstrap**](http://stats.stackexchange.com/questions/26088/explaining-to-laypeople-why-bootstrapping-works) to build CI’s around those EP values
* EP above only represent plays we've actually seen happen, but **they are just an estimate**.
* Want to make some **inferences** about the **range** of possible outcomes we DIDN'T see.
* Assume the plays we saw = drawn from some distribution of outcomes from alternate universes
* Can simulate this distribution by taking repeated samples w/ replacement from plays we DID see
* **This procedure doesn't assume anything about the distribution of the statistic we're interested in**
* CI built up gives some idea of how much variation we might expect in our estimator (EP) if we were to keep sampling from the distribution that generated the observations we already have.
* Look @ the 95% CI for the original EP:



* EP estimated using only 1st & 3rd quarters + close games falls outside of our CI quite often in the opponent's half of the field
* Note also uncertainty around EP is at its greatest the closer you get to your own end zone, + the least the closer you get to your opponent's endzone
* This = intuitive, but always good to know if an estimator has constant variance or not.