Lecture of Banking Analytics – lecture 7

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Scorecard Scaling

Point-Based Scorecard

- At this stage, if you train the regularized model, you have a logistic regression.
  - We want to go further with this.
  - Logistic model produces this ordered ranking
    - 0.99999 is the person most likely to default in my dataset
    - 0 is the person least likely to default in my dataset
    - Everyone in between is ordered so that 0.5 is the person that's neither likely, nor unlikely to default (assuming that I trained with balance).
  - The thing is, the 0.9999 points, are only relevant within the context of the dataset
  - So we have an incentive to make these numbers more informative and work better with all the other models that we are using in our business
  - We will be having an application scorecard, a behavioral scorecard, a model of risk of something,… and they all have a different "language" if I just use them as they come
    - E.g. 0.5 in logistic regression for application scorecard will be different from 0.5 on another logistic regression for behavior scorecard even though they both measuring the risk of not paying back the loan. One is measurement at origination when the loan just started, another is as loan is retained
  - Also, people don't like numbers in general
    - Numbers should make sense to them
    - In logistic regression for scorecard, number between 0 and 1, the higher the score means worse, more likely to default
    - We also want to turn this into a friendlier number that people can understand easily (higher scores means better)
  - So here is the incentive behind the point based scorecard
    - Note that this is only a friendly transformation without impacting our scorecard in any way
    - This is to calibrate the output so that several models all reflect the same risk with the same amount, so 100 points will mean the same across all the models that we have in the company no matter the risk.
    - We will calibrate them into a unique set of values
  - And it will look something like this

Characteristic Name	Attribute	Scorecard Points
AGE 1	Up to 26	100
AGE 2	26 - 35	120
AGE 3	35 - 37	185
AGE 4	37+	225
GENDER 1	Male	90
GENDER 2	Female	180
SALARY 1	Up to 500	120
SALARY 2	501-1000	140
SALARY 3	1001-1500	160
SALARY 4	1501-2000	200
SALARY 5	2000+	240

- So at this stage, we have the variables, neatly segmented. For each segment, we will assign a certain amount of points to them.
  - And higher amount of points means better
  - And the points themselves are going to mean something, and be related to a certain level of risk
- This is a completely arbitrary decision.
  - However, every company should use the same base values across all of their models

The things we need to decide

- We need to decide three numbers
  - Odds at a certain score
  - A base score
  - Points to double the odds
  - E.g. Odds of 50:1 at 600, and odds double every 20 points
    - If I have 50 people, all of them have the same score, then I expect one of them to be a defaulter.
    - For the base score (e.g. 600 in the example),
      - If this is the first scorecard, pick something to give me a neat range of points (e.g. from 200 to 1000)
      - If this is the second scorecard, I will calibrate it to the same values that I picked the first time so that the scorecards "speak the same language"
    - For the point to double the odds, in the example
      - For every 20 points, I double my odds
      - So at 600, my odds are 50:1
      - At 620, my odds are 100:1
      - At 640, my odds are 200:1

- At 630, my odds are $100 * 2^{10/20}: 1$
- Note that there is no guidance to picking the number, just want to make them reasonable

Shape of Scorecard

$$Score = Offset + Factor \times \ln(odds)$$

Example: Odds of 50:1 at 600 and 20 extra points for double odds

$$600 = \ln(50) * factor + offset$$
$$620 = \ln(100) * factor + offset$$

$$factor = 20 / \ln(2)$$
$$offset = 600 - factor * \ln(50)$$

(Hendrik Wagner)

- Recall that $odds = \frac{p(x)}{1-p(x)} = e^{X^T\beta}, where\ p(x) = \frac{1}{1+e^{-X^T\beta}}$
  - The $\ln(odds) = \sum \beta_i * WoE_i$ part is linearizing the scorecard

- Some math

$$score = \ln(odds) * factor + offset =$$
$$(\sum_{i=1}^{n}(woe_i * \beta_i) + \beta_0) * factor + offset =$$
$$(\sum_{i=1}^{n}(woe_i * \beta_i + \frac{\beta_0}{n})) * factor + offset =$$
$$\sum_{i=1}^{n}((woe_i * \beta_i + \frac{\beta_0}{n}) * factor + \frac{offset}{n})$$

  - So, every category will have the above expression
    - Note that the WoE is the only part that varies per person
  - Every category consists of
    - A neutral score, which is the same for everyone, this is the base score that gives you the average risk for every category, and this is

$$\frac{\beta_0}{n} * factor + \frac{offset}{n}$$

  - If the category score is above the neutral score, then the category is helping you predict more people in this category are non-defaulters
  - If the category score is below the neutral score, then the category is help predicting more defaulters.
  - Here, you can identify by how much this is helping you because of the Points to Double the Odds (PDO)

  - ✧ If an age of 24-40 gives you a score of 120, another category 40-50 is related to a scorecard of 160. What does this tell you about the relative risk between these two categories? How much less likely to default is a person in their 40-50 vs. someone between 25-40?
  - ✧ The points changed by 40, which means doubled twice, so a person between 25-40 is four times riskier than a person between 40 and 50
- ➢ In general, the formula is that between two categories, the difference of risk is going to be $2^{\frac{diff\ in\ score}{PDO}}$

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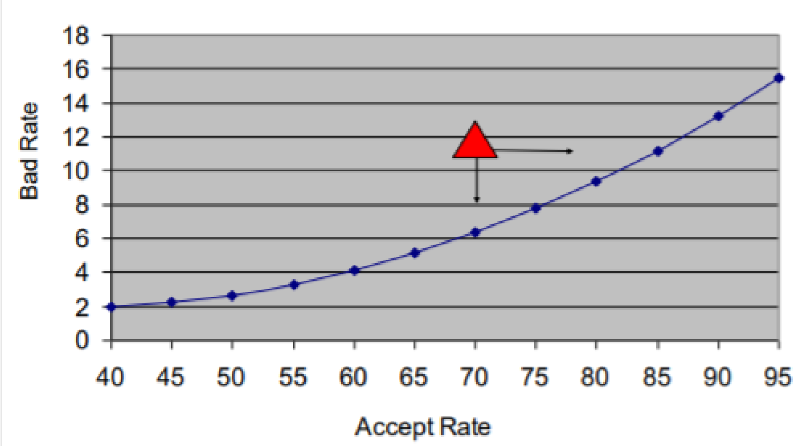
Cutoff Calculation

Setting the Classification Cutoff

- How do you decide who gets the loan and who doesn't? where is the cut?
  - ➢ I can set the cut to be 50%. 0.5 means that you are more likely to repay the loan than not. What's ignored?
    - ✧ The financial values should be taken into account, also risk averseness
  - ➢ But need some measure in order to understand whether the risk is sufficient or insufficient
    - ✧ Banks may vary the credit score based on the market conditions
  - ➢ We will choose a point on the strategy curve



  - ➢ If I accept 70% of the customers that come at my door, I am accepting a 6% default rate. But I am also leaving out 30% of customers that come for something
  - ➢ If you want a very low default rate, you will be leaving out 60% of customers that com and ask for a loan
    - ✧ The question is: is this enough to cover the income considering strategy and growth?
  - ➢ If wish to grow very quickly, have to take on a huge amount of losses
    - ✧ Probably pick a point to the right section for a few years
    - ✧ They are more interested in growing customers than making money because they are funded by investment capital
  - ➢ It also depends on the economic cycle

        - ✧ If we are at a very high part of the economic cycle, we will probably be more relaxed and accepting more people because default rates are low.
        - ✧ But if we are entering a crisis, naturally, banks will have incentive to withdraw unless supervisors are letting them to tap into the countercyclical buffer.
            - Then the banks will relax it a bit.
    - ➢ The risk area wants default rates to be low, so they push toward lower points and higher cutoffs
        - ✧ Higher cutoffs means that you need a greater credit score in order to get a loan, so it is constraint a little more
    - ➢ But markets want to sell more, they are pushing toward lower cutoffs
    - ➢ Basel says nothing about retail credit score and how they should be used, so banks make decisions based on their income and profits

- The second way besides strategy curve is to use the risk adjusted return on capital (RAROC) cutoff
    - ➢ This is to use cost and income to make decision
    - ➢ Income will create a credit score that will be the one with maximum profit
    - ➢ Calculate this using the capital that you have

$$RAROC = \frac{Revenues - Costs - EL \pm Other}{Capital}$$

$$RAROC = \frac{Revenues - Costs - PD.LGD.EAD \pm Other}{8\%.RW.EAD}$$

    - ➢ Not every bank can do this because you need good measures of revenues, cost, …
        - ✧ Real revenue will depend on interest rate, discounted cost of capital. Every customer will have their own interest rate
    - ➢ In general, banks will aim to simulate around 20-50 cutoffs and calculate aggregated profit over the test set (don't want this to be too optimistic).
    - ➢ How to do it
        - ✧ Adapt the circumstances to the reality of the company
        - ✧ Will have a certain amount of cost and profits that needs to be calculated
        - ✧ If find out that things should be calculated are not being calculated, then this I the time to start collecting those values.

Cutoff Point Tables

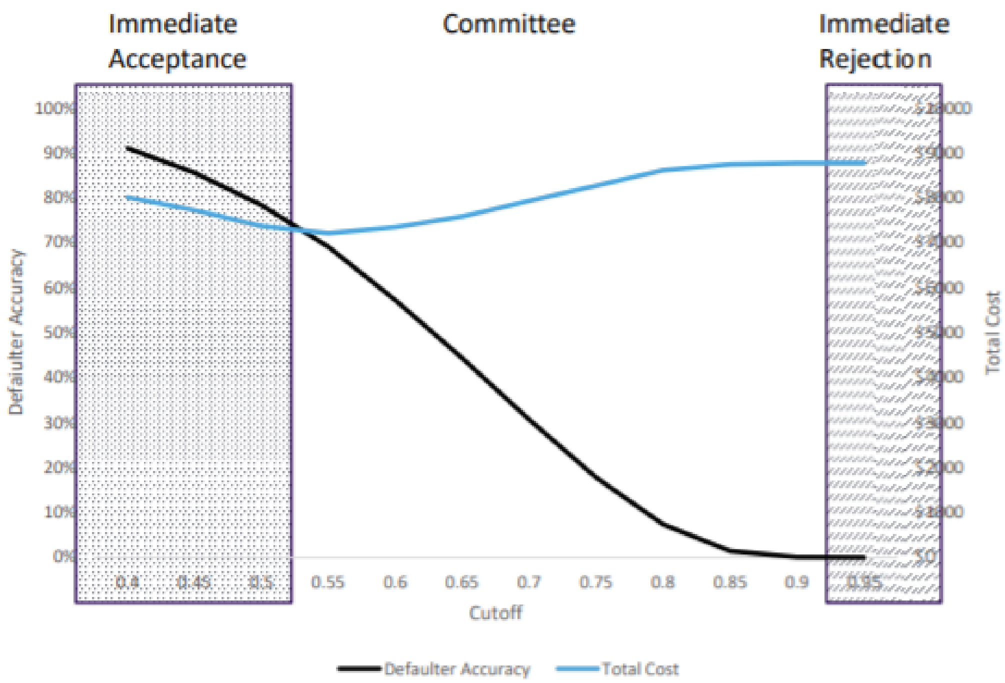
CutOff (T)	Accepted (%)	Accuracies (%)			Avg. Cost (€)		Total Cost (€ 000s)		
		Good	Defaulter	Total	Good	Defaulter	Good	Defaulter	Total
0.4	16.5%	19.2%	91.0%	38.1%	256	1789	6279	1731	8010
0.45	24.4%	28.0%	85.6%	43.1%	238	1614	5208	2513	7722
0.5	34.2%	38.7%	78.3%	49.1%	220	1402	4093	3278	7371
0.55	45.3%	50.5%	69.1%	55.3%	207	1226	3120	4092	7213
0.6	57.0%	62.1%	57.2%	60.8%	196	1102	2254	5092	7346
0.65	68.3%	72.8%	44.3%	65.4%	184	1009	1519	6062	7581
0.7	79.4%	83.0%	30.6%	69.3%	170	941	878	7052	7931
0.75	89.0%	91.4%	17.7%	72.1%	152	886	396	7870	8267
0.8	95.7%	96.7%	7.3%	73.3%	130	848	129	8481	8610
0.85	99.1%	99.3%	1.4%	73.6%	94	820	20	8725	8745
0.9	99.9%	99.9%	0.1%	73.8%	64	813	1	8770	8771

- Here we use the probabilities as cutoffs, but normally, we would use the credit scores

- For each cutoff, we need to calculate accuracy
  - First, we need to calculate the accepted rate
  - Trade-off between cutoff and accuracy in categorizing
    - If I make the cutoff as 0.4 (anything above 0.4 is 1), I will make more mistakes categorizing 0s to be 1s
    - Split this, and calculate accuracy of each category explicitly
      - Correctly predicted goods / total goods
      - Correctly predicted bads / total bads
    - Then you will see that you have very high accuracy in predicting the defaulters (the 1s) and very low accuracy in the non-defaulters
    - There is only a 38% accuracy, but it gets 90% defaulters correctly
      - That means, we accepted only 19.2% of the good customers and rejected 91% of bad customers (accepted 9% of bad customers)
  - Now we can calculate the cost
    - The average cost of being a defaulter vs. being a good borrower
      - In general, defaulters are a lot more expensive than good borrowers
      - We are talking about 3:1 to 10:1
      - One defaulter could eat the profit of 10 good borrowers
    - We need to calculate the cost of the respective borrower at default
      - LGD * EAD is the cost that we suffer
    - A good borrower, it will be the expected profits
      - (The interest rate – the cost of the funds) * time remaining
      - All the interests that they are supposed to pay you back discounted to the present
    - There may or may not be other factors, and it will depend on how good your measurement is
      - For retail, the LGD is 1, so all EAD is a loss
      - Which is not true, there could be some recoup
      - But the cost is going to be very high
- So we simulate and take a cut, in your test set, you can see if you correctly classify the defaulters or not and calculate how much money did you lose. Calculate the average for the cutoff for both defaulters and goods, you can calculate the total cost given the percentage of cases that you have
  - And you can calculate the average cost per customer
  - So for the 0.4 cutoff, the average profit for the goods is 256, the average defaulter brings 1789 of loss
  - Average cost for customer: 256 * P(customer is good) – 1789*P(customer is bad)
  - Average opportunity cost (use profit per customer) for good customer: total revenue from good customers / # of accepted good customers
  - Average cost for bad customer: total lost from defaulters / # of accepted bad customers
  - The total cost is 256 * # of missed good customers + 1789 * # of accepted bad customers
  - We want to find a cutoff that maximize that value
  - Most of the time, the banks will only take this as a guideline

Including a Refer Option

- This is another thing that banks, particularly the large ones do, is including their referral option
    - At 0.5, the model doesn't know whether a person is good or bad
    - So at 0.5, the bank will define a committee option, a referral option, where they do a more in depth evaluation



- However, this depends on what they can afford
    - Normally, banks cannot handle more than around 1-5%
- Should find the good balance between accuracy, cost and work load

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