EXECUTIVE SUMMARY/ABSTRACT:

Since the creation of TCGs (Trading Card Games), players try to use data available to help them win in a complex environment. As you pay a price for your decisions in game, it`s interesting to know if this prices adjusted correctly for what you are paying and what would be the most "efficient deal" in this scenario. Here we made a linear model to access if a minion card's mana cost in the game Hearthstone can be derived from the cards attributes: Rarity, Set, Attack, Defense and main mechanic. The model revealed different weights according to the factors taken into account and revealed interesting conclusions. The mechanics seem to be balanced with varying weights but without great differences. Cards class show more differences which may mean that balance of creatures varies between classes. Finally, we can conclude from this work that a card generally should never be judged in isolation and that diverse other effects and interactions should be taken into account to balance it as selecting the most efficient mechanics in the most efficient classes is not a guaranteed way to win.

INTRODUCTION:

In 2014, Hearthstone was released. It's a CCG (collectible card game) where two players starts with 30 life points. There are creatures, spells and weapons. In short, each of them do damage, recover life or make interactions.

Mechanics

The game is a virtual board game where players spend resources (mana) to play cards on the field. These cards have various features, all supposed to be correlated to the mana cost, where stronger cards (in the sense that they "beat" weaker ones) have a higher mana cost.

Picture 4: A minion card. It's composed of attack (yellow sword), health (red blood), mana cost(blue crystal), mechanics (text) class, race(in this case, a mech), class (blue border) and rarity(the blue jewel) (from https://hearthstone.gamepedia.com/Snowchugger)

Objective:

Explore the relation between a cards mana cost and its mechanics. To do this a linear model will be build which cost being explained by other variables that compose a card.

DATA:

The data come from a json file from the website https://hearthstonejson.com/docs/cards.html that contains data on all the cards released until today (6/1/18). This data was chosen for the

satisfactory amount of cards it addresses. A large dataset will help to make useful conclusions. It is publicly available and free to use. To treat the data the libraries rjags, rjson, coda and jsonlite were used. The database contains 1614 observations (cards) and 33 variables.

MODEL:

As cards are supposedly balanced (at least initially) based on its constituent attributes it`s interesting to check if this relation is linear and mana price can be derived from the cards values. A hierarquical model was chosen as to access if there are correlations among cards in some attributes like set of rarity. We choose uninformative normal priors as there are various variables and a substantial amount of observations making the data drive the results almost entirely.

The model is described below:

$$y_i \mid p_{mibirici}, \omega_{pmibirici}, \sigma \ \sim^{ind} \mathrm{N}(\omega_{mibirici}, \sigma)$$

$$\omega_{pmibirici} = \mathrm{c}_i + \mathrm{b}_1 * \mathrm{attack} + \mathrm{b}_2 * \mathrm{health} + \mathrm{b}_3 * \mathrm{race} + \mathrm{r}_i * \mathrm{rarity} + \mathrm{m}_i * \mathrm{mechanics}$$

$$\mathrm{m}_i \in (\text{list of mechanics}) \sim \mathrm{N}(\alpha, \sigma)$$

$$\mathrm{r}_i \in (\text{list of rarities}) \sim \mathrm{N}(\alpha, \sigma)$$

$$\mathrm{c}_i \in (\text{list of card classes}) \sim \mathrm{N}(\alpha, \sigma)$$

$$\alpha \sim \mathrm{N}(0.0, 1.0/1.0\mathrm{e}6)$$

$$\sigma \sim \mathrm{G}(2, 0.2)$$

The implementation in R was as follows:

```
mod_string = " model {
  for (i in 1:length(y)) {
    y[i] ~ dnorm(mu[i], prec)
    mu[i] = c[cardClass[i]] + b[1]*attack[i] + b[2]*health[i] + b[3]*race[i] + r[rarity[i]]*rarity[i] +
m[mechanics[i]]*mechanics[i]
  }

  for (j in 1:max(mechanics)) {
    m[j] ~ dnorm(a0, prec_a)
  }

  for (k in 1:max(rarity)) {
    r[k] ~ dnorm(a0, prec_a)
  }

  for (l in 1:max(cardClass)) {
    c[l] ~ dnorm(a0, prec_a)
  }

  a0 ~ dnorm(0.0, 1.0/1.0e6)
  prec_a ~ dgamma(1/2.0, 1*10.0/2.0)
  tau = sqrt( 1.0 / prec_a )

  for (j in 1:3) {
    b[j] ~ dnorm(0.0, 1.0/1.0e6)
  }

  prec ~ dgamma(5/2.0, 5*10.0/2.0)
  sig = sqrt( 1.0 / prec )
} "

set.seed(666)
data_jags = list(y=hs$cost,
                 mechanics=as.numeric(as.factor(unlist(hs$mechanics))),
                 race=as.numeric(as.factor(hs$race)),
                 cardClass=as.numeric(as.factor(hs$cardClass)),
                 attack=hs$attack,
                 health=hs$health,
                 rarity=as.numeric(as.factor(hs$rarity)))


params = c("a0", "b", "sig", "tau", "m", "r", "c")

mod = jags.model(textConnection(mod_string), data=data_jags, n.chains=3)


#run-----------------------------------
```

```
mod = jags.model(textConnection(mod_string), data=data_jags, n.chains=3)
update(mod, 2e3)

mod_sim = coda.samples(model=mod,
                       variable.names=params,
                       n.iter=5e4)
mod_csim = as.mcmc(do.call(rbind, mod_sim))


## convergence diagnostics--------------------
par(mar=c(1,1,1,1))
plot(mod_sim)

gelman.diag(mod_sim)
autocorr.diag(mod_sim)
autocorr.plot(mod_sim)
effectiveSize(mod_sim)

s <- summary(mod_csim)
ss <- s$statistics[,1]


barplot(ss,
        main="Comparison of factors",
             #xlab="custo ",
        #ylab="ataque ",
        horiz=TRUE,
        las=2,
        pch=19)

dic = dic.samples(mod, n.iter=1e3)
dic
```

RESULTS AND CONCLUSIONS:

FACTOR	MULTIPLYER	MEAN	SD	NAÏVE SE	TIME-SERIES SE
	A0	0.084295	0.07891	2.04E-04	4.35E-04
ATTACK	B[1]	0.448522	0.02442	6.30E-05	2.02E-04
HEALTH	B[2]	0.41022	0.02187	5.65E-05	1.90E-04
RACE (YES OR NO)	B[3]	0.03037	0.01872	4.83E-05	2.36E-04
DRUID	C[1]	0.567922	0.23575	6.09E-04	2.95E-03
HUNTER	C[2]	0.229165	0.23442	6.05E-04	3.24E-03
MAGE	C[3]	0.021578	0.23821	6.15E-04	2.93E-03
NEUTRAL	C[4]	0.278831	0.18838	4.86E-04	3.20E-03
PALADIN	C[5]	0.239214	0.24168	6.24E-04	2.87E-03
PRIEST	C[6]	0.043021	0.23514	6.07E-04	2.87E-03
ROGUE	C[7]	0.089925	0.23559	6.08E-04	2.90E-03
SHAMAN	C[8]	0.154219	0.23909	6.17E-04	2.93E-03
WARLOCK	C[9]	0.027902	0.22827	5.89E-04	3.04E-03
WARRIOR	C[10]	0.139671	0.23776	6.14E-04	2.89E-03
ADJACENT_BUFF	M[1]	1.341753	0.50982	1.32E-03	1.98E-03
AURA	M[2]	-0.1491	0.21048	5.44E-04	6.59E-03
BATTLECRY	M[3]	-0.12525	0.12849	3.32E-04	4.56E-03
CANT_ATTACK	M[4]	0.206315	0.17638	4.55E-04	2.98E-03
CANT_BE_TARGETED_BY_HERO_POWERS	M[5]	0.12632	0.14319	3.70E-04	2.46E-03
CANT_BE_TARGETED_BY_SPELLS	M[6]	-0.03243	0.12112	3.13E-04	2.04E-03
CHARGE	M[7]	-0.0663	0.06938	1.79E-04	1.88E-03

CHOOSE_ONE	M[8]	-0.07325	0.06329	1.63E-04	1.64E-03
COLLECTIONMANAGER_FILTER_MANA_EVEN	M[9]	-0.03918	0.14362	3.71E-04	1.28E-03
COLLECTIONMANAGER_FILTER_MANA_ODD	M[10]	-0.09261	0.12968	3.35E-04	1.18E-03
COMBO	M[11]	-0.07025	0.04809	1.24E-04	1.20E-03
DEATH_KNIGHT	M[12]	0.029038	0.10884	2.81E-04	9.97E-04
DEATHRATTLE	M[13]	-0.03111	0.03064	7.91E-05	1.05E-03
DIVINE_SHIELD	M[14]	0.004615	0.03298	8.52E-05	9.63E-04
ECHO	M[15]	-0.04382	0.04269	1.10E-04	8.84E-04
ENRAGED	M[16]	-0.00923	0.0346	8.93E-05	8.36E-04
FINISH_ATTACK_SPELL_ON_DAMAGE	M[17]	0.04073	0.07729	2.00E-04	7.26E-04
FORGETFUL	M[18]	-0.00614	0.04116	1.06E-04	7.20E-04
FREEZE	M[19]	0.003832	0.03901	1.01E-04	6.58E-04
GRIMY_GOONS	M[20]	-0.04447	0.04134	1.07E-04	6.32E-04
HEROPOWER_DAMAGE	M[21]	-0.05406	0.06321	1.63E-04	5.90E-04
INSPIRE	M[22]	-0.02164	0.02151	5.55E-05	6.00E-04
INVISIBLEDEATHRATTLE	M[23]	-0.02345	0.05762	1.49E-04	5.32E-04
JADE_GOLEM	M[24]	0.011097	0.04083	1.05E-04	5.30E-04
JADE_LOTUS	M[25]	-0.02258	0.03308	8.54E-05	5.08E-04
KABAL	M[26]	-0.05266	0.03184	8.22E-05	5.00E-04
LIFESTEAL	M[27]	-0.02618	0.01951	5.04E-05	4.91E-04
OVERLOAD	M[28]	-0.00888	0.01979	5.11E-05	4.67E-04
POISONOUS	M[29]	-0.00836	0.02032	5.25E-05	4.50E-04
RITUAL	M[30]	-0.01042	0.01631	4.21E-05	4.47E-04
RUSH	M[31]	-0.00183	0.01673	4.32E-05	4.28E-04
SPELLPOWER	M[32]	-0.00928	0.01506	3.89E-05	4.15E-04
START_OF_GAME	M[33]	-0.02154	0.02508	6.48E-05	3.95E-04
STEALTH	M[34]	-0.00414	0.01388	3.58E-05	3.96E-04
TAUNT	M[35]	-0.01173	0.01153	2.98E-05	3.91E-04
TOPDECK	M[36]	-0.03078	0.02703	6.98E-05	3.52E-04
TRIGGER_VISUAL	M[37]	-0.00904	0.01057	2.73E-05	3.66E-04
WINDFURY	M[38]	0.000906	0.01456	3.76E-05	3.48E-04
COMMON	R[1]	0.57085	0.36807	9.50E-04	1.27E-02
EPIC	R[2]	0.679812	0.1904	4.92E-04	6.35E-03
FREE	R[3]	0.235602	0.1342	3.47E-04	4.19E-03
LEGENDARY	R[4]	0.380262	0.09628	2.49E-04	3.17E-03
RARE	R[5]	0.148674	0.07517	1.94E-04	2.56E-03
	SIG	1.266355	0.02778	7.17E-05	8.27E-05
	TAU	0.5262	0.06174	1.59E-04	5.82E-04

Convergence was OK but correlation in the data was a problem. Even increasing the number of iterations did not seem so solve it.

Predictive performance does not seem good. Specific cards cannot be derived from this model, but this was expected, as some observations are clear outliers and should affect the results. Still the comparisons between the weights are valuable.

It is clear the relation of attack and defense, a card should have a little more health than attack to cost for its attack, which explains the minion in picture 2.

Interestingly there seems to be different weights by class. This maybe happened as classes have different number of creatures and values for them because of balancing issues. Therefore, these weights maybe reveal more about the classes than model the cards.

Another interesting conclusion is the similar magnitude of the weights of the mechanics. The model here ignores the various complexities of these mechanics.

Another interesting result is the relation of rarity and mana cost. Clearly, rarity plays a role on a card's cost. This has never been a secret as more rare cards have more complex mechanics, which makes the cards less and less "linear".

Finally, we can conclude that each part of the card indeed have a value to contribute to the mana cost and they differ greatly sometimes. These values may change over time due to power creep and balancing

Yet mana efficiency shouldn't tell us too much about the outcome of a game as it`s the direct result of comparison of cards and doesn't account for correlations.

Here we tried to evaluate what makes a card cost what it cost. The conclusion reached was that merely maximizing the effectiveness of the card's mana cost is not a guaranteed way to win every match.