How has the Brazilian Amazon been constructed as a problem - presidential speeches and transnational politics since 1985

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We need to protect the Amazon from foreign interests.

We need to exploit the Amazon's natural resources.

We need to provide better living standards for the people in the Amazon.

We need to preserve the Amazon as a standing ecosystem.

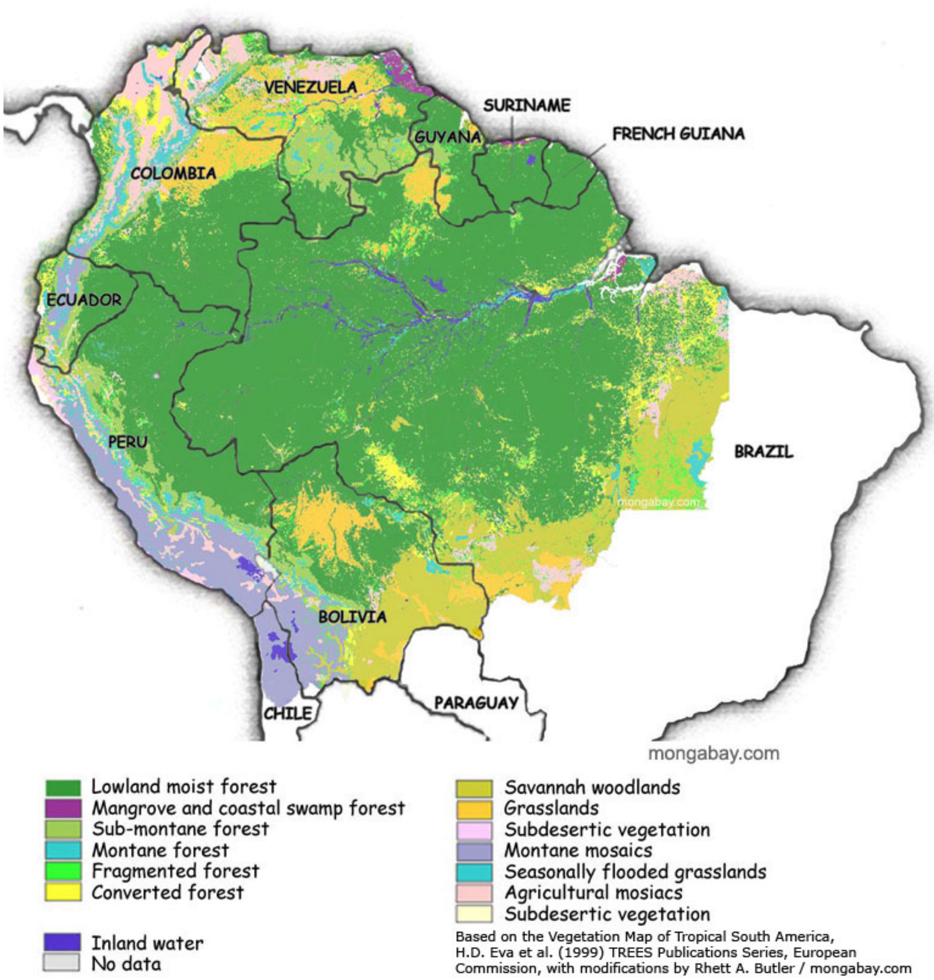

Figure 1: The Amazon Forest

Question

How the Brazilian Amazon has been constructed as a problem in transnational presidential speeches since 1985?

Data and methods

- Dataset containing all 6130 official speeches by presidents since 1985
- Subset of 2014 "amazonian statements"
- Location
- Hand-coding and supervised machine learning
- Can you think of some limitations with this approach?

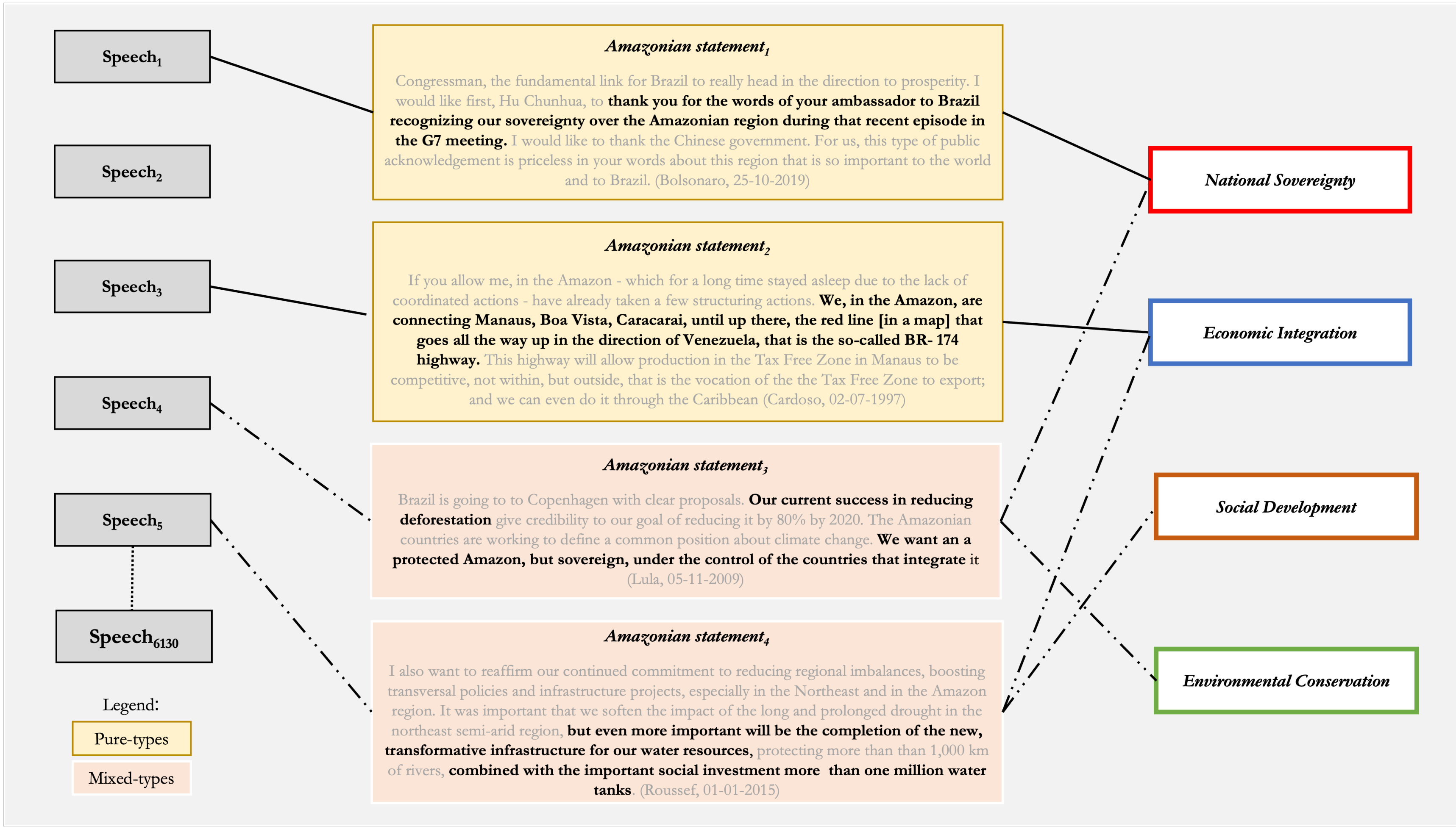

Figure 2: Operationalization of problem-constructions

```r
summary(ama)
```

```
##        ID        president              year        party          
##  Min.   :1001   Length:1895        Min.   :1985   Length:1895       
##  1st Qu.:1289   Class :character   1st Qu.:1996   Class :character  
##  Median :1522   Mode  :character   Median :2003   Mode  :character  
##  Mean   :1522                      Mean   :2003                     
##  3rd Qu.:1772                      3rd Qu.:2009                     
##  Max.   :2000                      Max.   :2021                     
##                                                                     
##    location          mixed_type          hand_coded         other       
##  Length:1895        Length:1895        Min.   :0.0000   Min.   :0.0000  
##  Class :character   Class :character   1st Qu.:0.0000   1st Qu.:0.0000  
##  Mode  :character   Mode  :character   Median :0.0000   Median :0.0000  
##                                        Mean   :0.4902   Mean   :0.2106  
##                                        3rd Qu.:1.0000   3rd Qu.:0.0000  
##                                        Max.   :1.0000   Max.   :1.0000  
##                                                                         
##               location_cat      AAI            km_to_manaus      def_year     
##  International        :165   Min.   :   1.65   Min.   :    0   Min.   : 4.571  
##  Amazonian States     :533   1st Qu.:   4.52   1st Qu.:    0   1st Qu.:10.129  
##  Amazonian Countries :153   Median :   6.41   Median : 1934   Median :14.286  
##  Brasilia             :597   Mean   : 239.93   Mean   : 1950   Mean   :15.366  
##  Non Amazonian States:444   3rd Qu.:  12.53   3rd Qu.: 2675   3rd Qu.:18.226  
##  NA's                 :  3   Max.   :2477.15   Max.   :15979   Max.   :29.059  
##                                                                              
##       area                                     mx_cat    election_year  
##  Min.   : 4571   Pure Economic Integration      :465   Min.   :0.000  
##  1st Qu.:10129   Other                          :399   1st Qu.:0.000  
##  Median :14286   Pure Environmental Conservation:275   Median :0.000  
##  Mean   :15366   Pure Social Development        :205   Mean   :0.258  
##  3rd Qu.:18226   Economic Conservation          :130   3rd Qu.:1.000  
##  Max.   :29059   Pure National Sovereignty      :105   Max.   :1.000  
##                  (Other)                        :316                  
```

```r
# library(skimr)
# skimr::skim(ama)
```

When Brazilian presidents speak about conservation in the context of the Amazon, where are they?

A simple logistic regression

Why do we use a logistic model and not a linear one here?

```r
ama_model <- filter(ama, location_cat != "Non Identified",
                         mx_cat != "Other Mixed-types") %>%
  mutate(con_vs_all = ifelse(mx_cat == "Pure Environmental Conservation", 1, 0),
         EI_vs_all = ifelse(mx_cat == "Pure Economic Integration", 1, 0),
         SD_vs_all = ifelse(mx_cat == "Pure Social Development", 1, 0),
```

```r
        sov_vs_all = ifelse(mx_cat == "Pure National Sovereignty", 1, 0))
# model
model_logit_con <- glm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                   family=binomial(link = "logit"), data = ama_model)
summary(model_logit_con)
```

```
##
## Call:
## glm(formula = con_vs_all ~ km_to_manaus + election_year + def_year +
##     AAI, family = binomial(link = "logit"), data = ama_model)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.3118  -0.5825  -0.5130  -0.4377   2.3245
##
## Coefficients:
##                  Estimate  Std. Error z value             Pr(>|z|)
## (Intercept)   -1.71845866  0.19066729  -9.013 < 0.0000000000000002 ***
## km_to_manaus   0.00011555  0.00002145   5.386         0.0000000719 ***
## election_year  0.28790781  0.15665954   1.838             0.066093 .
## def_year      -0.03173895  0.01129821  -2.809             0.004966 **
## AAI            0.00038679  0.00010404   3.718             0.000201 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1549.3  on 1841  degrees of freedom
## Residual deviance: 1497.3  on 1837  degrees of freedom
## AIC: 1507.3
##
## Number of Fisher Scoring iterations: 4
```

Estimates are in log odds... But what are log-odds?

Need an easy publication table? No worries!

```
stargazer::stargazer(model_logit_con, header = FALSE)
```

Table 1:

	Dependent variable:
	con_vs_all
km_to_manaus	0.0001^{***}
	(0.00002)
election_year	0.288^{*}
	(0.157)
def_year	-0.032^{***}
	(0.011)
AAI	0.0004^{***}
	(0.0001)
Constant	-1.718^{***}
	(0.191)
Observations	1,842
Log Likelihood	−748.648
Akaike Inf. Crit.	1,507.296
Note:	*p<0.1; **p<0.05; ***p<0.01

What about time effects?

```
pooled_ols <- plm::plm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                       data = ama_model, model = "pooling", index = c("year"))
summary(pooled_ols)
```

```
## Pooling Model
##
## Call:
## plm::plm(formula = con_vs_all ~ km_to_manaus + election_year +
##     def_year + AAI, data = ama_model, model = "pooling", index = c("year"))
##
## Unbalanced Panel: n = 37, T = 1-138, N = 1842
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -0.470289 -0.158090 -0.126625 -0.082295  0.953062
##
## Coefficients:
##                      Estimate    Std. Error t-value       Pr(>|t|)
```

```
## (Intercept)    0.1429802958  0.0235559575  6.0698 0.000000001552 ***
## km_to_manaus   0.0000178431  0.0000032303  5.5237 0.000000037934 ***
## election_year  0.0359069945  0.0199552120  1.7994      0.0721228 .
## def_year      -0.0033476666  0.0012965902 -2.5819      0.0099026 **
## AAI            0.0000552053  0.0000146958  3.7565      0.0001776 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    233.24
## Residual Sum of Squares: 226.09
## R-Squared:      0.030665
## Adj. R-Squared: 0.028555
## F-statistic: 14.5286 on 4 and 1837 DF, p-value: 0.00000000001099
```

```
fixed <- plm::plm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                  data = ama_model, model = "within", index = c("year"))
summary(fixed)
```

```
## Oneway (individual) effect Within Model
##
## Call:
## plm::plm(formula = con_vs_all ~ km_to_manaus + election_year +
##     def_year + AAI, data = ama_model, model = "within", index = c("year"))
##
## Unbalanced Panel: n = 37, T = 1-138, N = 1842
##
## Residuals:
##      Min.   1st Qu.    Median   3rd Qu.      Max.
## -0.729676 -0.166751 -0.117960 -0.045981  0.970345
##
## Coefficients:
##                  Estimate   Std. Error t-value    Pr(>|t|)
## km_to_manaus 0.0000152831 0.0000033197  4.6037 0.000004441 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    220.46
## Residual Sum of Squares: 217.9
## R-Squared:      0.011612
## Adj. R-Squared: -0.0086599
## F-statistic: 21.194 on 1 and 1804 DF, p-value: 0.0000044405
```

```
# Not a good choice here, why? (tip: is this a balanced panel)

random <- plm::plm(con_vs_all ~ km_to_manaus + election_year + def_year + AAI,
                   data = ama_model, model = "random", index = c("year"))
summary(random)
```

```
## Oneway (individual) effect Random Effect Model
##    (Swamy-Arora's transformation)
##
## Call:
## plm::plm(formula = con_vs_all ~ km_to_manaus + election_year +
```

```
##     def_year + AAI, data = ama_model, model = "random", index = c("year"))
##
## Unbalanced Panel: n = 37, T = 1-138, N = 1842
##
## Effects:
##                    var  std.dev share
## idiosyncratic 0.120789 0.347547 0.981
## individual    0.002288 0.047836 0.019
## theta:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00934 0.26150 0.35206 0.33835 0.42343 0.47400
##
## Residuals:
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -0.46769 -0.16706 -0.12348 -0.00009 -0.07395  0.95696
##
## Coefficients:
##                    Estimate    Std. Error z-value     Pr(>|z|)
## (Intercept)    0.1648304527  0.0331734180  4.9688 0.0000006739 ***
## km_to_manaus   0.0000166369  0.0000032727  5.0835 0.0000003706 ***
## election_year  0.0271240068  0.0298012337  0.9102      0.36274
## def_year      -0.0044176296  0.0018997506 -2.3254      0.02005 *
## AAI            0.0000516826  0.0000220758  2.3411      0.01922 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Total Sum of Squares:    228.22
## Residual Sum of Squares: 223.14
## R-Squared:      0.022236
## Adj. R-Squared: 0.020107
## Chisq: 38.5979 on 4 DF, p-value: 0.000000084344
```

```
# Better, but not a good choice here, why? (tip: is this a balanced panel)
```

Nominal outcome (depenedent) variables, multinomial is the name of the game!

```
library(nnet)
# model
model_multi <- nnet::multinom(mx_cat ~ location_cat + election_year + def_year + AAI,
                              data = ama_model, model = TRUE, trace = FALSE)
# summary statistics
summary(model_multi)
```

But very hard to interpret as there are, often, multiple reference categories… Above the reference categories are Pure Economic Inegration in International settings?!

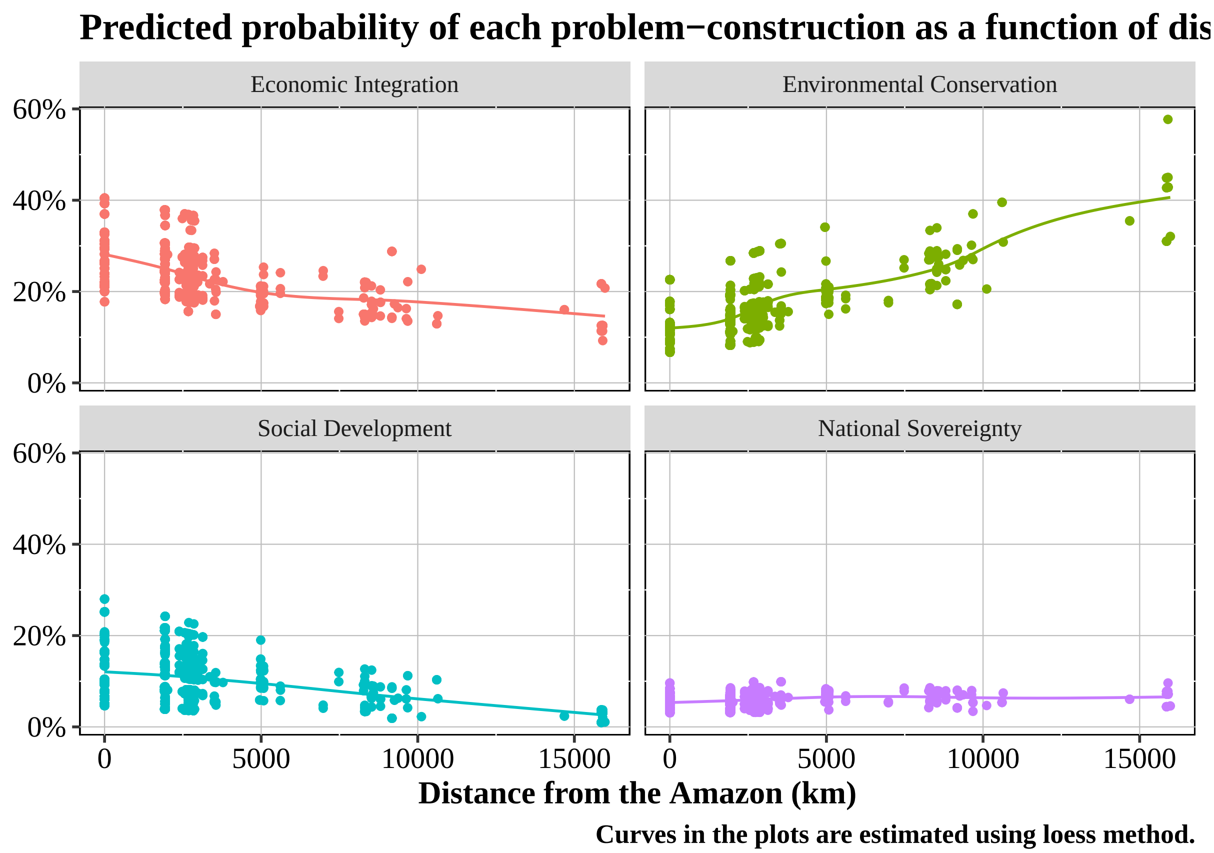

Figure 3: Logistic Regression predicted values

Can you see the relationship?

The Amazon multi-level game: boasting policy outside

Table 2: Logistic Regression Models

	Dependent variable:			
	Conservation	Economic Integration	Social Development	Sovereignty
	(1)	(2)	(3)	(4)
Distance from the Amazon in 1000s of km	0.115554***	−0.056590**	−0.101285**	0.009384
	(0.021453)	(0.023979)	(0.039849)	(0.038080)
Election year	0.287908*	−0.022328	0.328917*	−0.448696*
	(0.156660)	(0.132762)	(0.171163)	(0.269325)
Yearly Deforestation	−0.031739***	0.040870***	−0.072349***	−0.031859*
	(0.011298)	(0.008404)	(0.013232)	(0.016768)
Yearly Inflation	0.000387***	−0.000231**	−0.000205	0.000215
	(0.000104)	(0.000104)	(0.000151)	(0.000177)
Constant	−1.718459***	−1.568837***	−0.909845***	−2.300558***
	(0.190667)	(0.159988)	(0.213791)	(0.280849)
Observations	1,842	1,842	1,842	1,842
Log Likelihood	−748.648200	−1,022.790000	−620.264400	−399.290500
Akaike Inf. Crit.	1,507.296000	2,055.579000	1,250.529000	808.581000
Note:				*p<0.1; **p<0.05; ***p<0.01

Why distances to Manaus by 1000km?