The Muslim Paradox: Gender Gap in STEM Vocations

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FOREWORD

The percentage of male STEM (Science, Technology, Engineering and Mathematics) graduates is significantly and consistently higher than that of females in all of the developed western societies without exception. This has been a matter of concern and debate over the last few decades.

Two opposing monolithic views attempt to explain this phenomenon. In a nutshell, these are very biased versions of the classic nature versus nurture dichotomy.

On the one hand, there are those who claim that traditional gender stereotypes and conditioning are to blame. On the other, certain borrow arguments from evolutionary biology in order to suggest that women would be relatively but intrinsically less interested in system-centred subjects as opposed to human-centred activities.

As a scientist and father of two inquisitive Montessori girls, this is a subject that has intrigued me for a while.

So I have decided to crunch the numbers myself and just hear what they have to say.

I am no expert in statistic, data analysis, economy, sociology or any other relevant discipline. Everything I may say must be taken with a grain of salt.

As a matter of fact, my intention is not to reveal the “truth” but, rather, humbly provide a few hints on how to proceed.

Let me advance for the impatient that the main conclusion of this little study is actually that there is not enough relevant data to jump into any conclusions.

So what I am going to do it is to pretend there is and suggest a couple of things we could do if such data actually existed.

THE DATA

Conventionally, we could refer to the variables we want to win some knowledge about as **targets** and the descriptors we use to gain knowledge on those targets as **features**. We will be using machine learning models in order to try and explain those targets on the basis of a few selected features.

As targets (Table 1) we have chosen the percentage of female STEM graduates with respect to the total number of STEM graduates. Obviously, this does not inform us about how many of those female graduates are going to actually pursue a STEM career or of the challenges they may face.

However, one has to start somewhere and, for illustrative purposes, we have preferred to keep things as simple as possible. The chosen targets are easy to measure and quantify and there is available data for over 120 countries. Furthermore, these are targets that inform us about intentions and, therefore, values.

Table 1. Targets: Female share of graduates in each discipline (percentages).

Abbreviation	Discipline	Source of the data	URL
STEM	Science, Technology, Engineering and Mathematics	UNESCO Institute for Statistics	http://data.uis.unesco.org/
SCI_MATH	Science and Mathematics	UNESCO Institute for Statistics	http://data.uis.unesco.org/
ENG	Engineering	UNESCO Institute for Statistics	http://data.uis.unesco.org/
ICT	Information and communication technologies	UNESCO Institute for Statistics	http://data.uis.unesco.org/

As potential features (Table 2) we have chosen a variety of descriptors that can be classified into the following categories: Economic indicators, development indexes, general values, attitudes towards women, attitudes towards science, perception of science employability prospects.

Then the machine learning (ML) algorithms were allowed to pick up the features with the highest explanatory ability for each target. Given that certain features are either correlated or not entirely linearly independent, the algorithm choosing a particular one over another may not be relevant. What matters most is the category to which the feature belongs and the kind of correlation with the targets, be it direct or inverse.

Table 2. Features explained.

Abbreviation	Description	Source of the data	URL
	Economic		
GDPPC	Gross Domestic Product per capita	The World Bank	https://data.worldbank.org/indicator/NY.GDP.MKTP.CD
unemployment	Unemployment rate (2010-2020 average)	The World Bank	https://data.worldbank.org/indicator/SL.UEM.TOTL.ZS
	Development Indexes		
HDI	Human Development Index	UN Development Programme	http://hdr.undp.org/en/content/table-3-inequality-adjusted-human-development-index-ihdi
IHDI	Inequality-adjusted Human Development Index	UN Development Programme	http://hdr.undp.org/en/content/table-3-inequality-adjusted-human-development-index-ihdi
FHDI	Human Development Index (Women)	UN Development Programme	http://hdr.undp.org/en/content/table-4-gender-development-index
GDI	Gender Development Index	UN Development Programme	http://hdr.undp.org/en/content/table-4-gender-

			development-index
GII	Gender Inequality Index	UN Development Programme	http://hdr.undp.org/en/content/table-5-gender-inequality-index-gii
GINI	Gini coefficient	The World Bank	https://data.worldbank.org/indicator/SI.POV.GINI
		Values	
Christians	Percentage of Christians	Pew Research Center	https://www.pewforum.org/datasets/2020/
Muslims	Percentage of Muslims	Pew Research Center	https://www.pewforum.org/datasets/2020/
Unaffiliated	Percentage of non-religious individuals	Pew Research Center	https://www.pewforum.org/datasets/2020/
		Attitudes towards women (percentages)	
GSNI0	Gender Social Norms Index - no bias	UN Development Programme	http://hdr.undp.org/en/gsni
GSNI1	Gender Social Norms Index - 1 bias or more	UN Development Programme	http://hdr.undp.org/en/gsni
GSNI2	Gender Social Norms Index - 2 biasses or more	UN Development Programme	http://hdr.undp.org/en/gsni
GSNI_edu	Gender Social Norms Index - Educational bias	UN Development Programme	http://hdr.undp.org/en/gsni
GSNI_eco	Gender Social Norms Index - Economic bias	UN Development Programme	http://hdr.undp.org/en/gsni
GSNI_pol	Gender Social Norms Index - Political bias	UN Development Programme	http://hdr.undp.org/en/gsni
GSNI_phi	Gender Social Norms Index - Physical integrity bias	UN Development Programme	http://hdr.undp.org/en/gsni
		Attitudes towards science (percentages)	
SCI_TRUST-High	Hight trust in science	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-global-monitor/2018
SCI_TRUST-Medium	Medium trust in science	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-global-monitor/2018
SCI_TRUST-Low	Low trust in science	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-global-monitor/2018
SCI_BENEFITS-Enthusiast	Enthusiast about science benefits	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-

			global-monitor/2018
SCI_BENEFITS-Included	Personal benefit from scientific advances	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-global-monitor/2018
SCI_BENEFITS-Excluded	No personal benefit from scientific advances	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-global-monitor/2018
SCI_BENEFITS-Sceptic	Sceptic about science benefits	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-global-monitor/2018
	Perceived employability prospects		
SCI_JOBS-Increase	Local science jobs expected to increase	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-global-monitor/2018
SCI_JOBS-Decrease	Local science jobs expected to decrease	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-global-monitor/2018
SCI_JOBS-Neither	Local science jobs expected to remain invariable	Wellcome Global Monitor	https://wellcome.org/reports/wellcome-global-monitor/2018
stemt	Share of STEM graduates	UNESCO Institute for Statistics	http://data.uis.unesco.org/

THE TARGETS

Figure 1. Share of female STEM graduates per country.

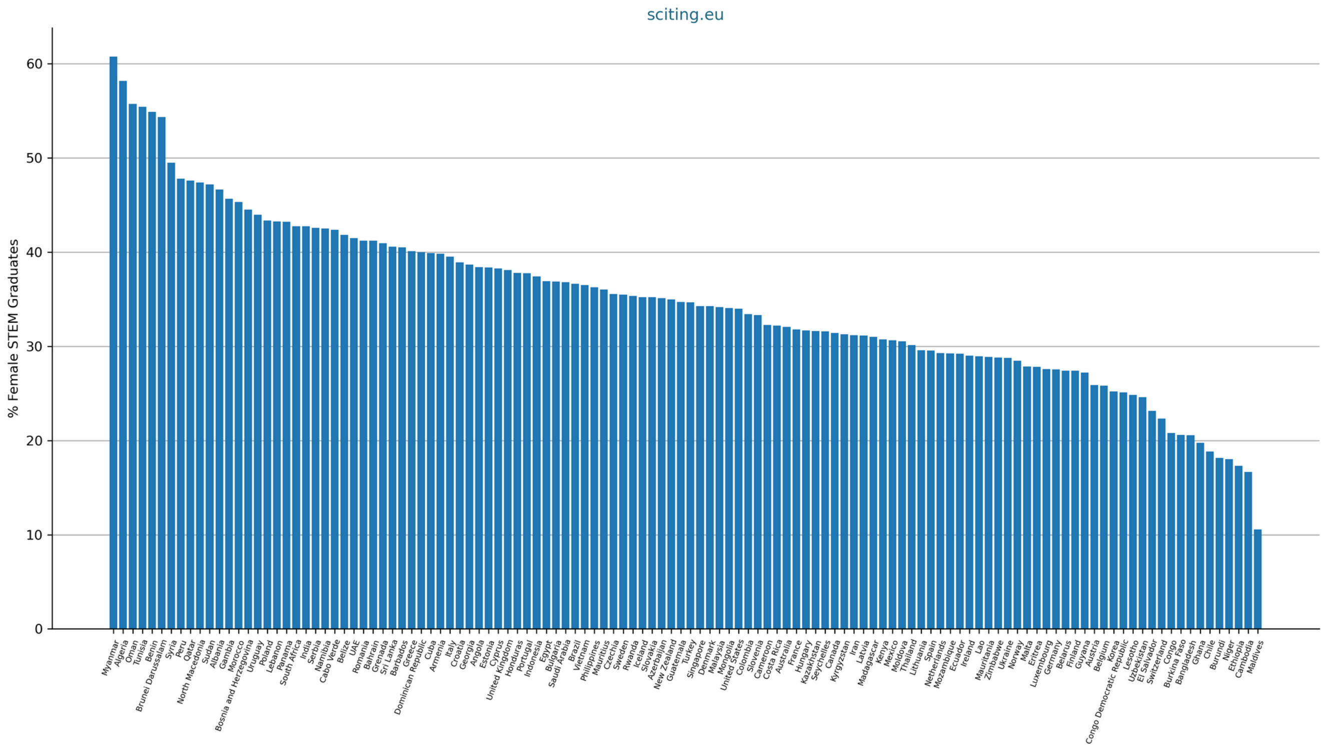


Figure 2. Share of female Science and Maths graduates per country.

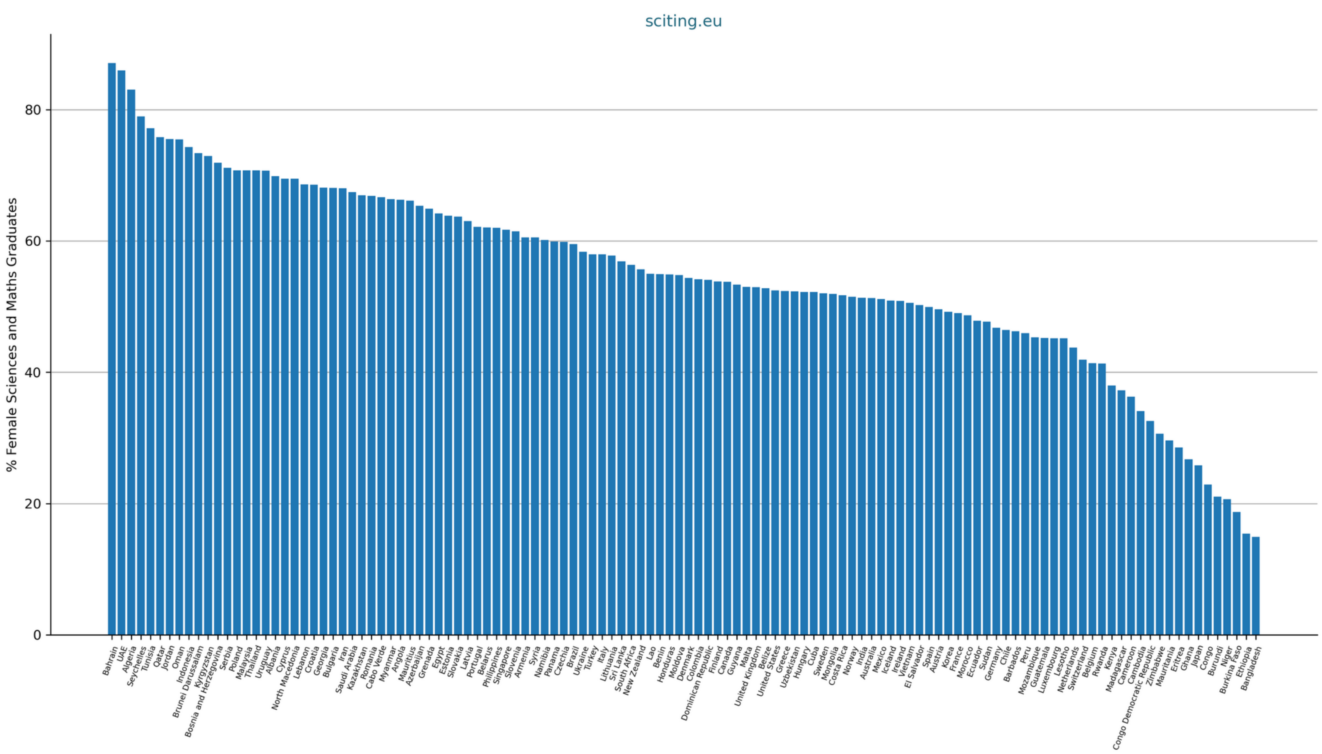


Figure 3. Share of female Engineering graduates per country.

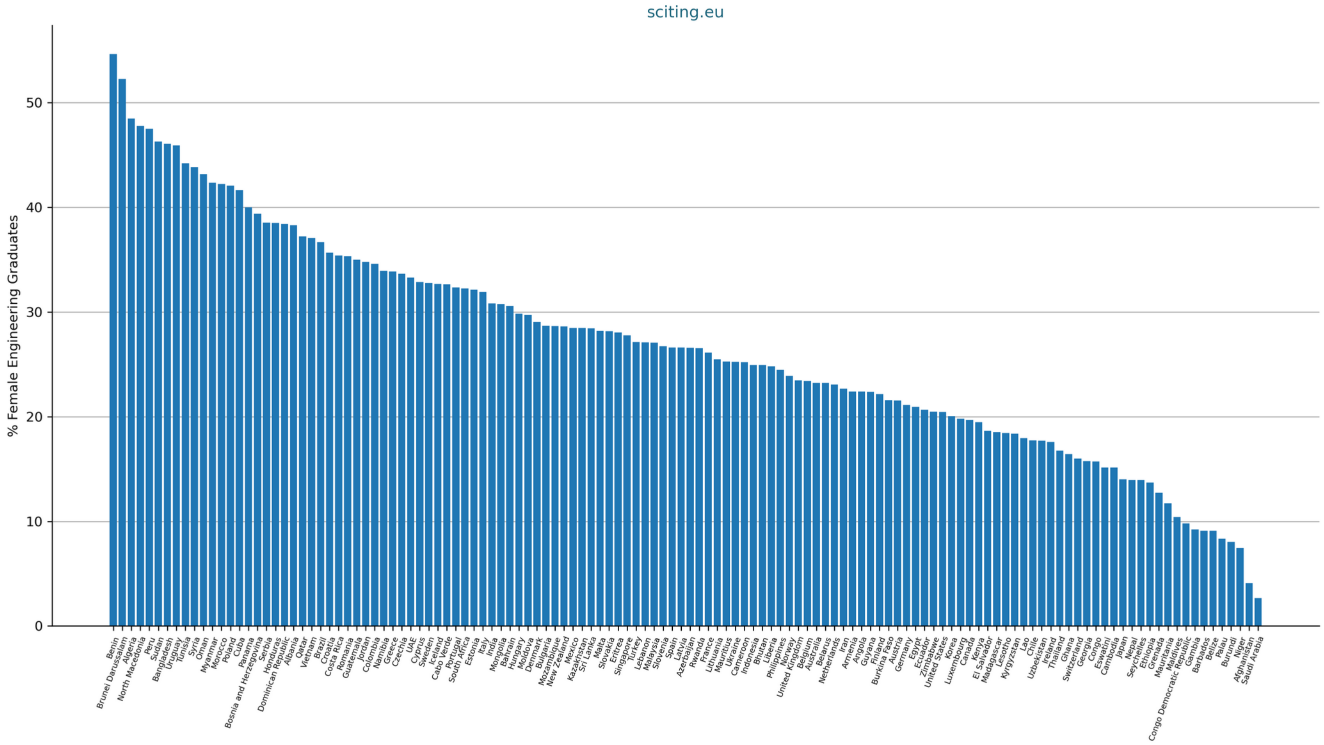
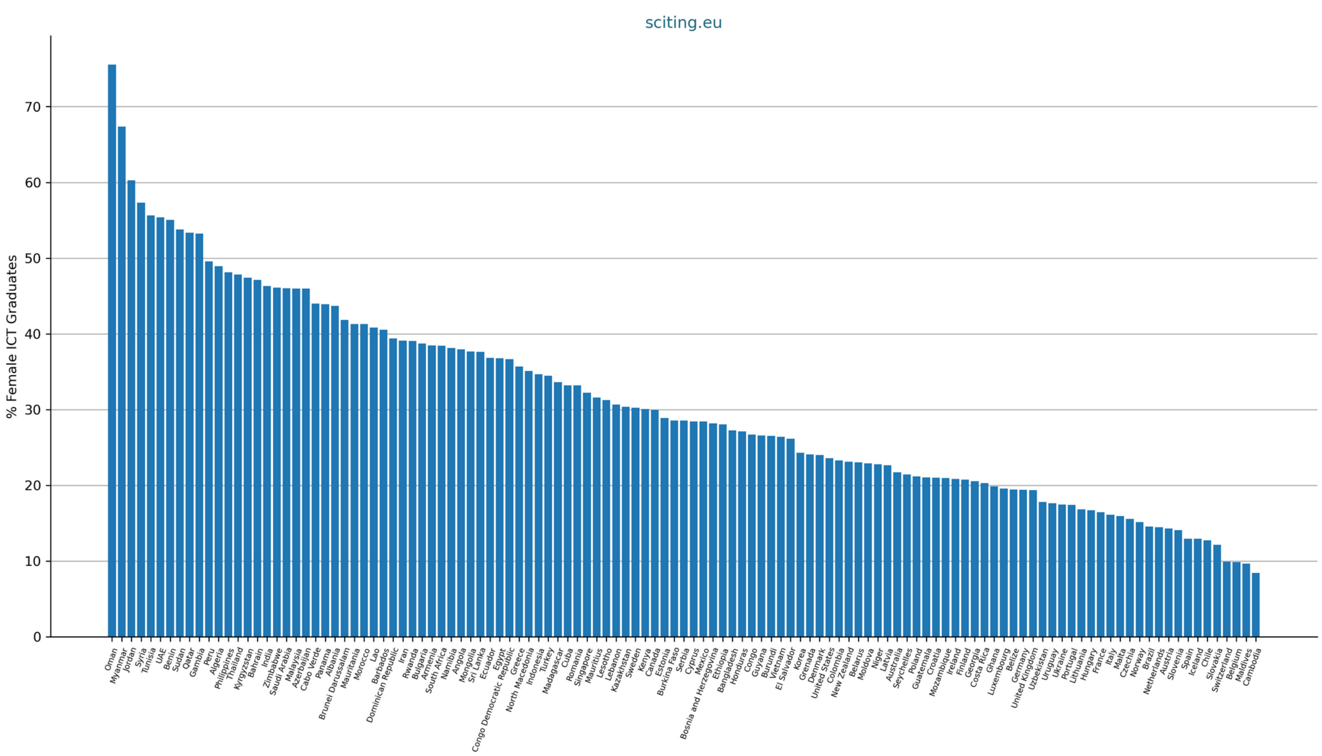


Figure 4. Share of female ICT graduates per country.



A quick look to the above plots already enable us to notice some trends:

- European and other developed western nations are never at the top (nearly or over 50 % female STEM graduates). They typically rank in the middle (significant gender imbalance), except for ICT where they are largely towards the bottom (large gender imbalance).

- The countries with the largest percentage of female STEM graduates are primarily low-to-medium-GDP economies and so are those at the bottom.

- Most countries at the top are typically those predominantly Muslim. In fact, the European country with the largest share of female STEM graduates for each subdivision is often Bosnia and Herzegovina (51 % Muslim population). Hence the tittle of this report, which is purposefully provocative.

METHODS

Data handling

The different datasets were download them from the respective sources (Tables 1 and 2) and parsed with a Python script in order to produce a single CSV file containing all the targets and descriptors for each country.

The raw data was not modified with three exceptions:

- Not all the values correspond to the same year. The latest available value was considered. In fact, it could have been better to use the opposite criteria and select older values in many instances (given that, for instance, social prestige and attitudes may lag behind economical changes substantially).

- The data for female engineers in Argentina was old and very suspicious (over 100 % increase from one year to the next) and therefore the country was entirely removed from the analysis.
- Protectorates and now fully sovereign countries have also been removed.

Data points with null data were removed. This resulted on the dataset being shrunk from *ca.* 130 data points to 50. The smaller data set and limiting factor is the Gender Social Norms Index from the United Nations, which is only available for 50 countries.

Feature selection

The data set was randomly split between a training set (80 %) and a testing set (20 %).

A Random Forest model (RF) was build with scikit-learn 0.24.1 with default parameters except for n_estimators=100. Hyperparameters were not optimised because the goal of this project is not to produce and optimal model but to find the most relevant features.

Initially all the features were considered and ranked according to feature_importances_.

With such scarce data, the results of the machine learning training greatly depend on how representative the training set is with the respect to the testing set. Therefore, the importances were reported as an average of 100 random splits.

Then, the features were added to the model one by one according to the previously determined ranking. Only features improving the the correlation between the real and predicted target values measured as R-squared averaged over 100 random splits were kept.

Finally, a new model was built including only the optimal features for each target.

RESULTS

The produced models seem to be both accurate and robust for ICT but not for STEM, Science+Maths and Engineering (figures 5-8).

Figure 5. Accuracy of the RF model for all STEM disciplines combined.

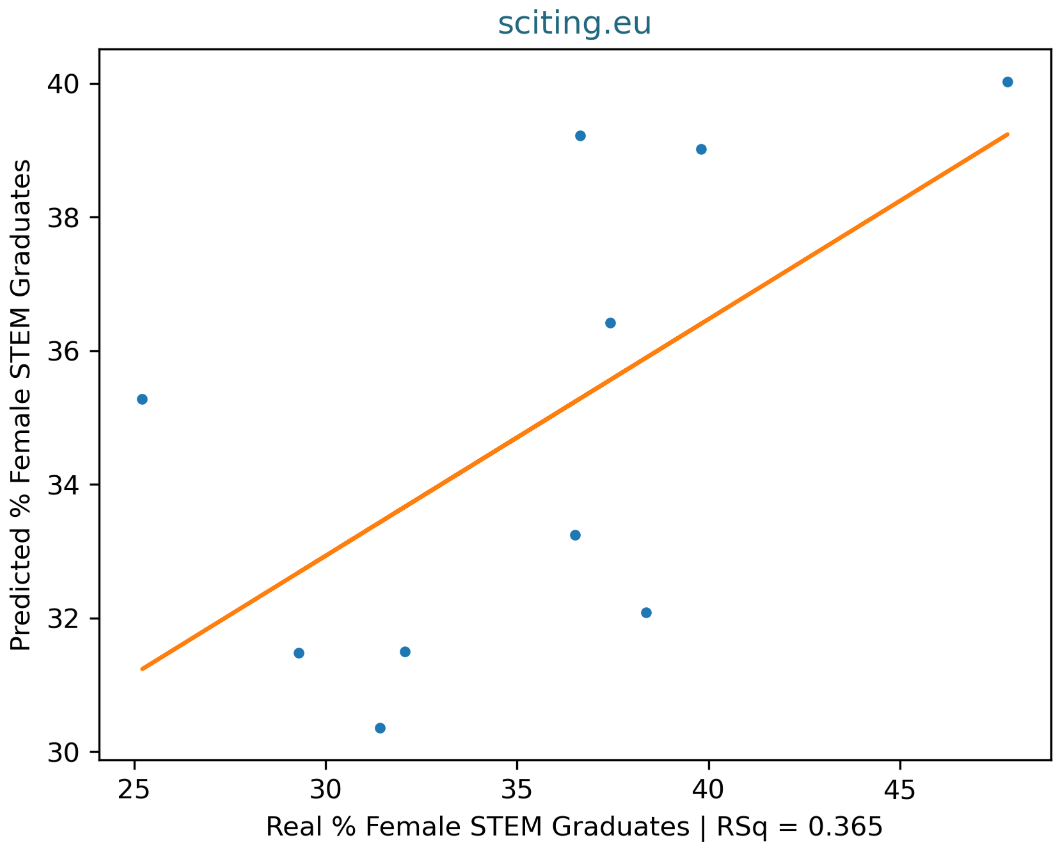


Figure 6. Accuracy of the RF model for SCI_MATH.

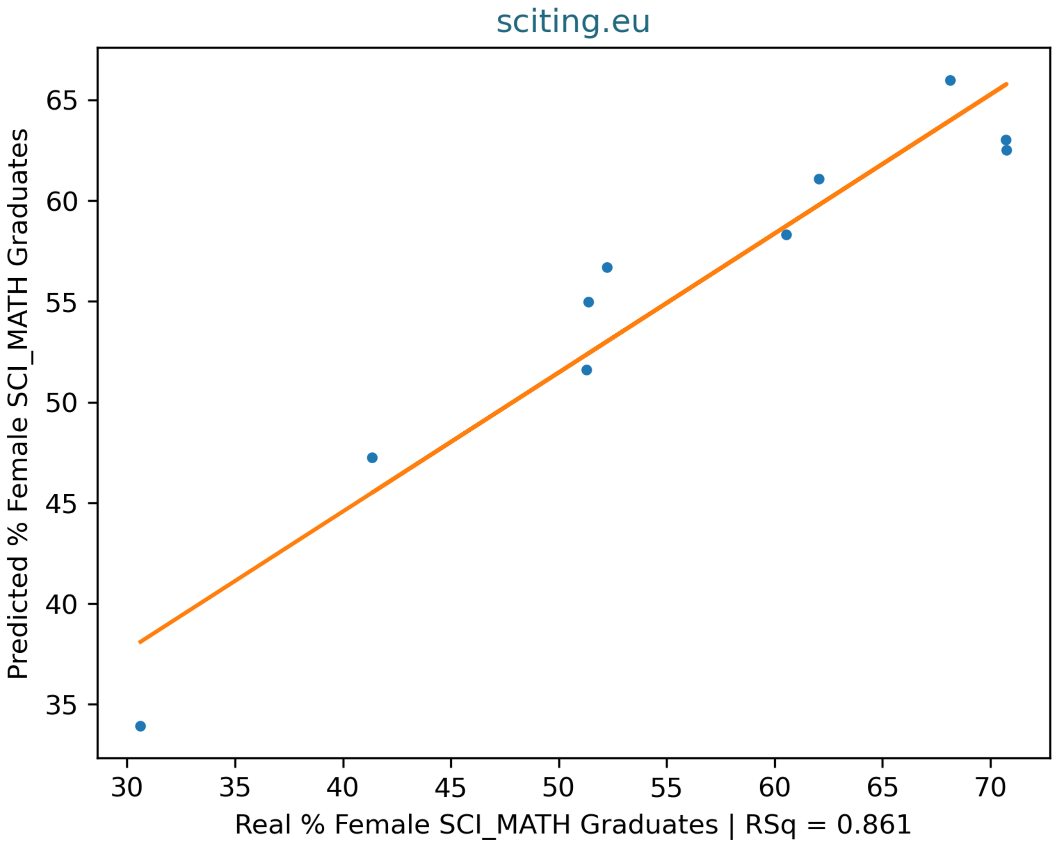


Figure 7. Accuracy of the RF model for Engineering.

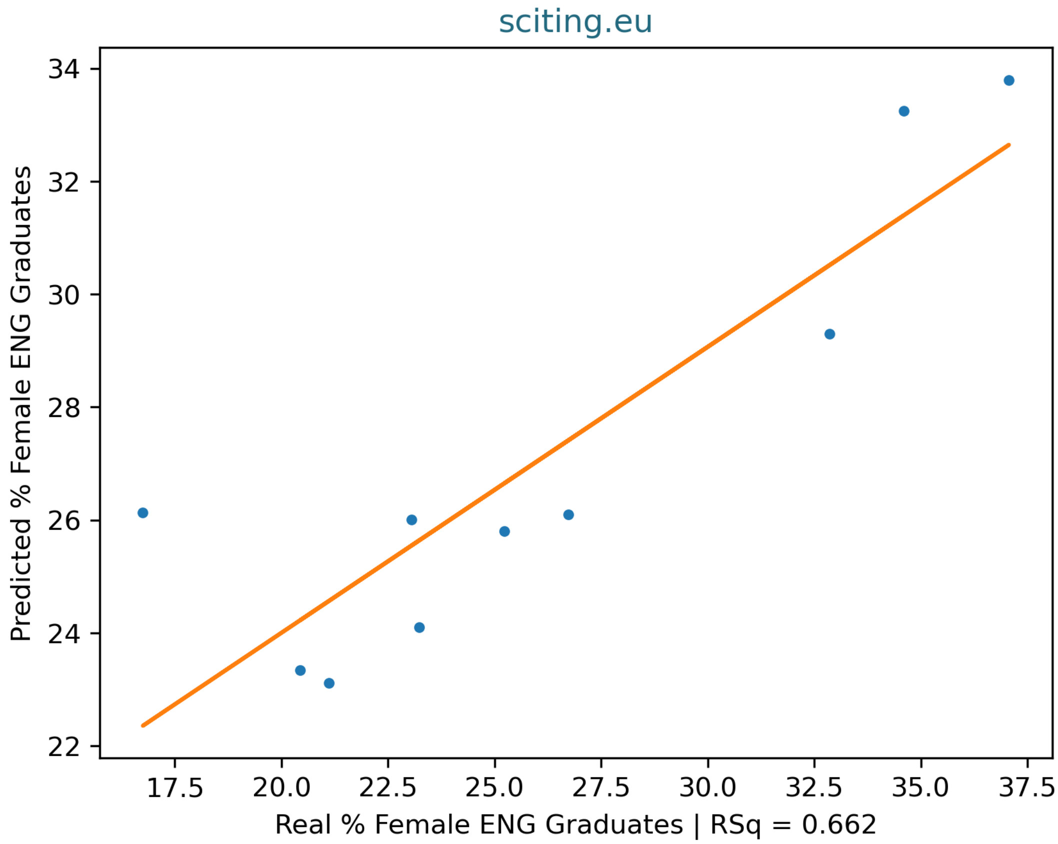
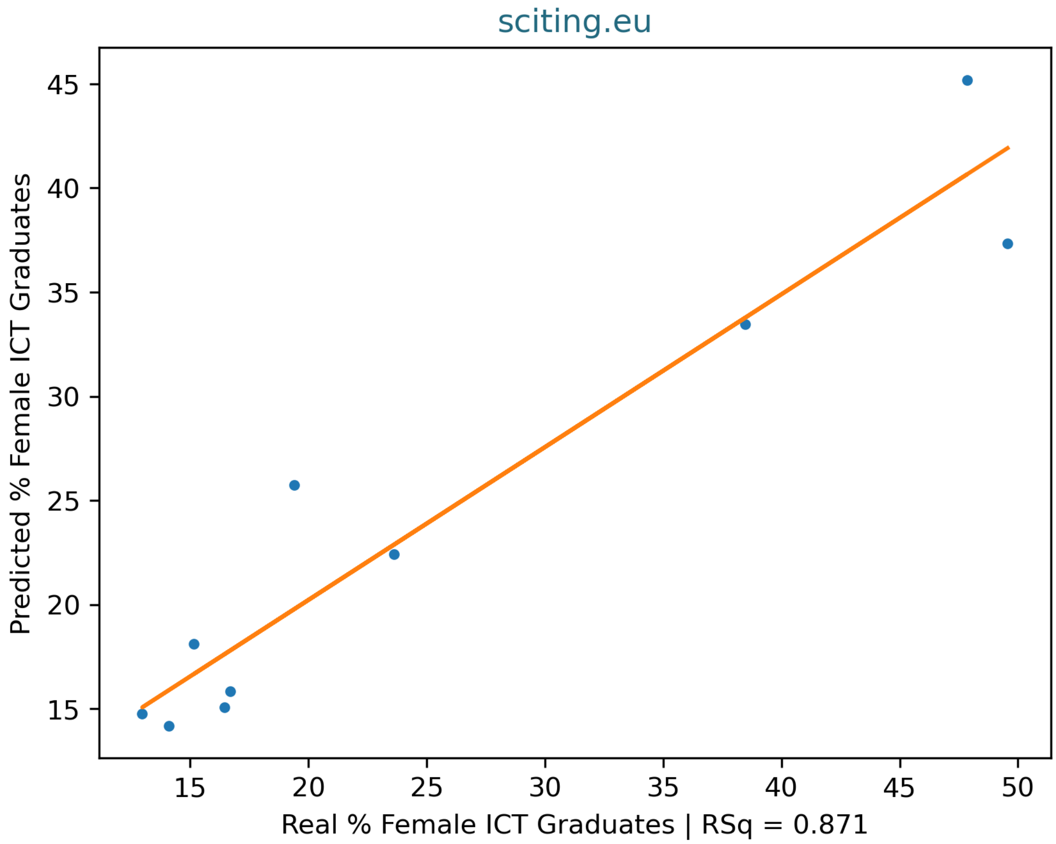


Figure 8. Accuracy of the RF model for ICT.



ANALYSIS

No single feature possesses predictive power. However, the most accurate and robust model (ICT) can be trained with as few as three features: SCI_JOBS-Decrease, Unaffiliated and GSNI_phi.

As stated earlier, more important than the specific features is the category to which they belong. As a trend, we observe that the three more important categories are:

- Job market expectations. How feasible people think that it is to find a job in STEM with respect to other areas. The feature with the most powerful descriptive capabilities is SCI_JOBS-Decrease. The correlation is inverse. The more people are convinced that STEM jobs will become scarce in the future, the less girls will choose a STEM career (not only in absolute terms, but also with respect to boys). Another such descriptor that comes out systematically is stemt, which measures the percentage of STEM graduates with respect to other disciplines. Stemt is probably linked to job market expectations (how easy it is to find a job and how good is the salary) but maybe also to the social prestige of the given job (which does not always correlate with the objective circumstances of the market). Again, the more people choose STEM careers, the higher the percentage of girls is going to be with respect to boys. It would seem that, at least in conservative societies with traditional values, girls would be more sensitive than boys to whatever the social consensus may be.

- General values. The percentage of girls in STEM is inversely proportional to the percentage of non-religious people in a given country. Indeed, Unaffiliated is the most descriptive feature but others also rank above average. In this case, the countries with more girls in STEM are not the extremely traditional ones but those which are very traditional without being at the foremost extreme of the spectrum. This means mostly Muslim countries but also a couple in Latin America and Europe. Typically countries with low-to-medium GDP (or rich in terms of GDP but with relatively high economic inequality) and very religious.

- Attitudes towards women. Several Gender Social Norms Index-related features contribute to the quality of the models. As it happens with the general values, the countries with the higher proportions of female STEM graduates are in the middle of the spectrum leaning towards the traditionalist end. Not the most socially and economically advanced countries and not the most oppressive ones, but countries with a strongly traditional mindset without being utterly alienating.

- Finally, the general prestige of science as such seems to play a smaller but somehow significant role. Namely SCI_BENEFITS-Enthusiast (people who are optimist regarding the societal benefits of science) comes up relatively frequently even though it does not score very high with respect to, for instance, the job market expectations, which is the group of features with the highest descriptive power.

Two final considerations with respect to features:
- Typically, discrete specific features seem to be more descriptive than aggregate indexes. For instance, from the Wellcome Trust questionnaire, specific questions such as job market expectations work a lot better than any meta-scores, which, in this case, do not appear to possess much predictive value.

- Furthermore, maybe due to intrinsic reasons or maybe to the tiny size of the dataset, extreme answers, be them positive or negative, are preferable to their more mild and nuanced complementary alternatives. For instance SCI_JOBS-Decrease or SCI_BENEFITS-Enthusiast.

THE MUSLIM PARADOX

So, going back to the original question, why do so many Muslim countries score so high? I do not know, but they seem to be on the right position of the spectrum in several metrics.

- They are not developed countries but they are economically functional. People can reasonably hope to find a job after graduation (at home or abroad).

- Technical professions seems to have high prestige (even if not so science as such). In terms of salary they may be preferable to other options, but this is one of the questions that needs to be verified.

- They have traditional values that push young people towards traditionally prestigious professions. Women seem to be more sensitive to social consensus and prestige.

- In less developed countries primarily middle to higher class students attend college. This may well introduce a certain bias favouring certain disciplines. Yet another hypothesis needing verification.

- They have a traditional view of gender roles but women are not prevented from going to college. They may be even encouraged to do so.

The last point raises a good number of other questions, the more relevant being: do all those female STEM graduates actually enter the job market after graduation? Is their purpose to become financially independent or are there other motivations?

SUGGESTIONS FOR FUTURE WORK

If we are to develop a realistic understanding of our environment we need reliable data. Relevant information needs to be collected from as many countries as possible.

Some data such as the percentage of women that find a STEM job after graduation can be gathered from governmental sources. Other by devising appropriate questionnaires and asking people directly.

REPOSITORY:

The Python 3 scripts and most of the data have been uploaded to GitHub:

https://github.com/mirix/stem