# Mining the Trend of the Most Frequently Used Programming Languages and Tools of the Last Decade

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#### 1 Motivation

As a computer science student, knowing the programming languages and development tools that have been frequently used in industry for the past years is important because it would help me understand what skillsets I would need to gain to prepare myself for the workforce. I am interested to know the trend of the most used programming languages and tools in the past 10 years. Is there a particular collection of programming languages and tools that have been frequently used by a certain demographic? Knowing the trend of programming languages and tools would not only benefit students and professionals to keep track of the latest technology for career development, but also would create opportunities for businesses and educational institutions in the software and programming field.

#### 2 Literature Survey

There are some well-established indicators for the most popular languages on the web that are free to the public. The TIOBE index gives the most popular 100 programming languages which is updated monthly and is based on the number of hits on various websites [9, 14]. The IEEE Spectrum provides a similar indicator that is generated from the popularity among the IEEE members and developers, the employer demands and the current trend [2, 3]. However, both indicators currently do not cover programming tools such as development environment or frameworks.

Studies have been done in finding trends in programming tools using Stack Overflow posts. Approximately 11 million user question and answer posts of Stack Overflow have been used to find the most popular languages, tools and topic trends

between 2014 and 2015 by topic modeling [10]. Trends of NoSQL database from 2008 to 2017 have been investigated by using the normal interest score of Stack Overflow posts [6]. Moreover, posts on Stack Overflow that are related to C, Java and Python over a 14-year period have been studied and interestingly the user's country and reputation are included in trend analysis [11].

Surveys have also been used to find trends. The Stack Overflow Developer Survey has been used in investigating gender insights [12] and finding the most used programming languages and tools for 23 different IT roles [5]. Interestingly, a study that collected data from surveys and multiple sources from schools and industries in 1993, 1998 and 2003 formed a regression model that illustrated the trend [4].

I would like to explore the trends of the most frequently used programming languages and tools with demographic data to see if there are any interesting patterns. The Apriori algorithm can be used to mine frequent itemsets [7] and has been applied to find trends in major selection among university students [1] and frequent patterns in human drug addiction behavior [8]. This would be an exciting tool to use in this study to find hidden patterns.

#### 3 Data Set

The data set of this study is retrieved from Stack Overflow Annual Developer Survey webpage [13] and surveys from 2015 to 2024 are included, which is 10 sets in total.

The number of responses for each survey from 2015 to 2024 are 26086, 56030, 51392, 98855, 88863, 64461, 83439, 73268, 89184 and 65437, respectively. The number of attributes for each survey from 2015 to 2024 are 45, 65, 153, 128, 84, 60, 40, 70, 68 and 87, respectively.

The attributes among these surveys are not exactly the same, but there are seven shared concepts, which are occupation/devtype(nominal), country(nominal), years of coding/programming experience(ordinal/ratio),

compensation/salary(ordinal/ratio),

education(nominal), languages worked in the past year(nominal), and tools worked in the past year(nominal). Even though the 10 surveys also share languages and tools that one wants to work in the future, these attributes are not included in the study because we would like to focus on the most used languages and technologies, instead of the languages and technologies that people most want to work with.

#### 4 Proposed Work

My research plan is similar to the study that analyzed the most used languages and technologies to the 2020 Stack Overflow Developer Survey [5], yet it will be different because this study includes data across 10 years as well as exploring frequent patterns.

Since we are combining 10 sets of surveys, we need to make sure that only the shared attributes are included, and they should be consistent among surveys. Data preprocessing is crucial and going to be challenging in our case.

# 4.1 Data Cleaning

"NA" There values are some in the compensation/salary attribute. It would be logical if the compensation is not applicable if the respondent is a student, however there may be cases where the respondent does not want to reveal this information. However, we cannot assume that the "NA" response equal to \$0 compensation for students. Therefore, if the total number of "NA" values is significant, then we either need to take caution when explaining the results or consider dropping that attribute in the merged dataset.

#### 4.2 Data Transformation

Data transformation needs to be performed on the shared attributes before data integration. Although all the surveys have the compensation/salary and the years of coding/ programming experience attributes, some of the surveys ask for numeric response yet some provide a selection of ranges (i.e., ordinal) for respondents. To have a consistent attribute type for the integrated data set, there will be data discretization performed.

Moreover, even if the share attribute is ordinal, the selections may not be the same size. For example, the answer selections of the years of coding/programming experience attribute are "less than 1 year", "1-2 years", "2-5 years", "6-10 years" and "11+ years" in the 2015's survey. However, in the 2018's survey, the available answers are "0-2 years", "3-5 years", "6-8 years" and continue every two years until "30+ years". Therefore, data transformation is needed to ensure the interval labels of the same attribute are consistent among surveys.

There are multiple attributes (e.g., framework and version control system) in each survey that can be joined into a new attribute (e.g., programming tools). Therefore, there will be new attribute creation and in general, the final attributes will represent the seven shared concepts mentioned above.

## 4.3 Data Integration

After ensuring that the shared attributes are consistent across 10 surveys, the shared attributes will be combined into one large data set and the rest of the attributes will be discarded.

# 4.4 Derive The Most Used Languages

To see the trend of the most used languages in the past 10 years, we can retrieve the programming languages with the highest frequency by year from the data set. Furthermore, we can dig deeper by looking at different occupation/devtype, years of coding/programming, compensation, education and country.

## 4.5 Derive The Most Used Tools

Programming tools with the highest frequency can be calculated by year to observe the trend of the most used tools in the past 10 years. Additionally, we can

examine this with different occupation/devtype, years of coding/programming, compensation, education and country.

# 4.6 Derive Frequent Patterns with Apriori

To find the frequent patterns, each respondent's most worked with languages, tools, occupation/devtype, years of coding/programming, compensation, education and country data will be combined into an item. The frequent itemsets can be found after running all items with the Apriori algorithm.

## 5 Evaluation Methods

There will be limited validation methods for this study because the aim of this study is not establishing a prediction model, which means it would not be logical to reserve partial data for validation. The frequent patterns that we will find using Apriori may overlap with the most frequent languages and tools using descriptive statistics, which may serve some degree of validation. Also, frequency histograms can be generated to check the accuracy of the result.

#### 6 Tools

The Python language and Pandas, NumPy and Matplotlib libraries will be used to manage and perform statistical analysis on large datasets as well as to provide visualization of results.

## 7 Milestones

Data collection and search for common attributes have been done. I plan to finish data cleaning, data transformation and data integration before October 28th, to obtain the most used languages and tools by November 4th, and to complete the frequent patterns by November 11th.

# 7.1 Milestones Completed

Potential attributes of each survey have been reviewed by their data types and the proportion of the Nan value, and then transformed to ensure consistency among the 10 surveys.

Moreover, multiple choice answers have been converted into lists to facilitate data analysis process. String format answers that contain multiple values

separated by semicolons are extracted and transformed into a Python list. For example, Linux-based; Windows" would be transferred into ["Linux-based", "Windows"]. On the other hand, values of several potential attributes are merged into a list to represent a shared concept. For example, there is a collection of questions that is related to Training and Education in the 2015 survey which each question represents a different multiple choice (e.g., Training & Education: No formal training, Training & Education: Boot camp or night school and Training & Education: BS in CS.). In this case, answers to each question of the same collection are collected by a loop and added to the same list.

Currently the preferred operating system and preferred development environment have been retrieved as two separate attributes. This is because the data cleaning process started from the 2015 survey which has these two attributes separated from the collection of languages and technologies attributes. Moreover, they are listed as two independent attributes in most of the surveys.

The rule for dropping Nan value for each survey is when any row/respondent has Nan values for all tool and languages related attributes (excluding the preferred operating system and the preferred development environment). The reason for dropping data is because the goal of our study is to understand the most used languages and tools in the past 10 years, and it would not make sense to include entries with Nan values in all languages and tools related attributes. The drop percentage per survey ranges from 0.81% to 28.13% among these 10 surveys, which leaves a total of 634598 valid data for analysis.

Compensation/Salary is one of the seven share concepts, however it is not included in the final attributes because of two reasons. First, not all 10 surveys explicitly asked the respondents to enter their salary in a specific currency. Even though some surveys asked about the daily currency used, this does not guarantee that the salary entered is in the same currency. Furthermore, more than half of the surveys have over 30% of Nan values in salary, which implies that there is a certain amount of data that cannot be

interpreted. Therefore, considering the issue raised above, compensation/salary is not included in the final attributes of the merged dataset.

#### 7.2 Milestones Todo

Next, the 10 sets of surveys will be integrated into one dataset to derive the most frequently used languages, and the most frequently used tools. Because the preferred operating system and preferred development environment have been retrieved as two separate attributes, we may need to derive the most frequently used operating system and the most frequently used development environment as well.

#### 8 Results so far

There are eight final attributes of the merged survey, which are Occupation, Country, Education, Years\_Coding, OS (i.e., Operating system), Dev\_Env (i.e., Development environment), Year and Tools. The final attributes and the corresponding attributes that have been used in each survey are shown in Figure 1.

	2015 Survey	2016 Survey
Occupation	Occupation	occupation
Country	Country	country
Education	Training & Education*	education
Years_Coding	Years IT / Programming Experience	experience_range
os	Desktop Operating System	desktop_os
Dev_Env	Preferred text editor	dev_environment
Year	Self-created	
Tools	Current Lang & Tech*, Source control used*	tech_do

Training & Education\* is a collection of attributes that represent different categorical choices, such as Training & Education: No formal training and Training & Education: BS in CS.

Current Lang & Tech\* is a collection of attributes that represent different categorical choices, such as Current Lang & Tech: Android and Current Lang & Tech: Hadoop.

Source control used\* is a collection of attributes that represent different categorical choices, such as Source control used: Git and Source control used: Bitkeeper.

	2017 Survey	2018 Survey
Occupation	DeveloperType, WebDeveloperTy pe, MobileDeveloper Type, NonDeveloperTy pe	DevType
Country	Country	Country
Education	FormalEducation, MajorUndergrad, EducationTypes	FormalEducation, UndergradMajor, EducationTypes
Years_Coding	YearsProgram	YearsCoding
OS		OperatingSystem
Dev_Env	IDE	IDE
Year	Self-created	Self-created
Tools	HaveWorkedLan guage, HaveWorkedData base, HaveWorkedFra mework, HaveWorkedPlatf orm	LanguageWorked With, DatabaseWorked With, PlatformWorked With, FrameworkWork edWith

	2019 Survey	2020 Survey
Occupation	DevType	DevType
Country	Country	Country
Education	EdLevel, UndergradMajor, EduOther	EdLevel, UndergradMajor
Years_Coding	YearsCode	YearsCode
OS	OpSys	OpSys
Dev_Env	DevEnviron	
Year	Self-created	Self-created
Tools	LanguageWorked With, DatabaseWorked With, PlatformWorked With, WebFrameWorke dWith, MiscTechWorked With	LanguageWorked With, DatabaseWorked With, PlatformWorked With, WebframeWorke dWith, MiscTechWorked With, NEWCollabTools WorkedWith

	2021 Survey	2022 Survey
Occupation	DevType	DevType
Country	Country	Country
Education	EdLevel, LearnCode	EdLevel, LearnCode
Years_Coding	YearsCode	YearsCode
os	OpSys	OpSysProfession al use, OpSysPersonal use
Dev_Env	NEWCollabTools HaveWorkedWith	NEWCollabTools HaveWorkedWith
Year	Self-created	Self-created
Tools	LanguagesHave WorkedWith, DatabaseHaveWorkedWith, PlatformHaveWorkedWith, WebframeHaveWorkedWith, MiscTechHaveWorkedWith, ToolsTechHaveWorkedWith,	LanguageHaveW orkedWith, DatabaseHaveWo rkedWith, PlatformHaveWo rkedWith, WebframeHaveW orkedWith, MiscTechHaveW orkedWith, ToolsTechHaveW orkedWith, OfficeStackAsyn cHaveWorkedWith, OfficeStackSync HaveWorkedWith

	2023 Survey	2024 Survey
Occupation	DevType	DevType
Country	Country	Country
Education	EdLevel, LearnCode	EdLevel, LearnCode
Years_Coding	YearsCode	YearsCode
OS	OpSysProfession al use, OpSysPersonal use	OpSysProfession al use, OpSysPersonal use
Dev_Env	NEWCollabTools HaveWorkedWith	NEWCollabTools HaveWorkedWith
Year	Self-created	Self-created
Tools	LanguageHaveW orkedWith, DatabaseHaveWo	LanguageHaveW orkedWith, DatabaseHaveWo

rkedWith,	rkedWith,
PlatformHaveWo	PlatformHaveWo
rkedWith,	rkedWith,
WebframeHaveW	WebframeHaveW
orkedWith,	orkedWith,
MiscTechHaveW	EmbeddedHave
orkedWith,	WorkedWith,
ToolsTechHaveW	MiscTechHaveW
orkedWith,	orkedWith,
OfficeStackAsyn	ToolsTechHaveW
cHaveWorkedWit	orkedWith,
h,	OfficeStackAsyn
OfficeStackSync	cHaveWorkedWit
HaveWorkedWith	h,
,	OfficeStackSync
AISearchHaveW	HaveWorkedWith
orkedWith,	,
AIDevHaveWork	AISearchDevHav
edWith	eWorkedWith

# Figure 1: Attributes of the merged data and their corresponding attributes in each survey

From Figure 1, we can see that the 2017 Survey does not have a question regarding the preferred operating system (i.e., the OS attribute) and the 2020 Survey does not ask about the preferred development environment (i.e., the Dev\_Env attribute), which we should keep in mind during data interpretation.

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