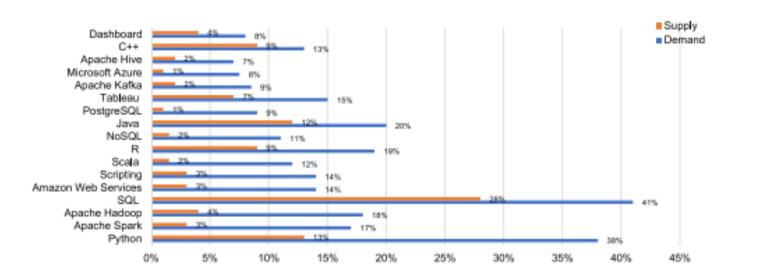


Background/Problem

Many job postings consist of requirements that are unrealistic for those entering the labor market, especially within the data science field. Learning the skills and knowledge necessary for this industry can help firms and the labor force tackle the growing employment gap.

Northeastern professors received a grant to develop a data science curriculum for reskilling workers in the manufacturing industry.

Our team was tasked with helping to connect learners with the courses and modules that best fit their goals.



Data Science-related skills demand, supply, and gaps

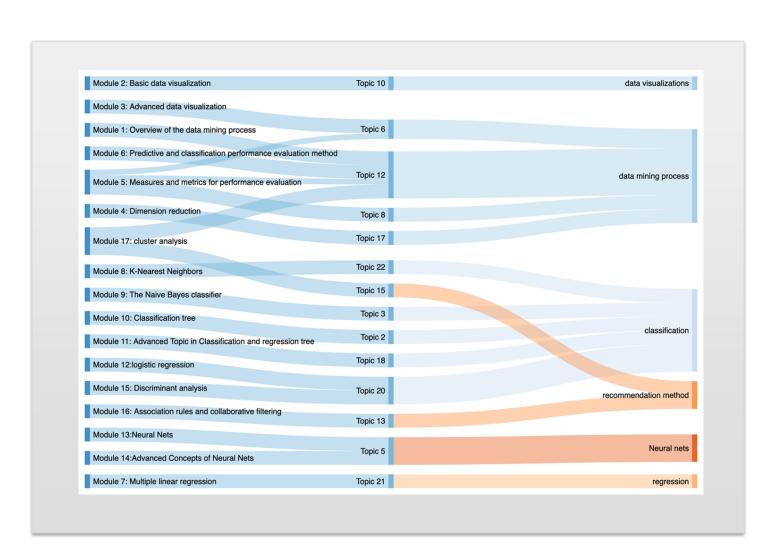
Graphic Credit: Guoyan Li

Methodology

Employing the design process, the team decided to create an automated course recommendation system that aligns specific modules from the curriculum to users based on their specific profiles – their abilities and desires.

A graduate student on the IMPEL team, Guoyan Li, used an algorithm (called LDA) to process many resources associated with data science in manufacturing to produce a list of topics. This algorithm also provided the team with correlation values to relate each topic to specific modules seen in the Topic-Module matrix.

With correlation values provided by the team, the undergraduate Capstone team had the subject matter experts fill out the Skill-Topic matrix to relate skills and domains to specific topics



Graphic Credit: Guoyan Li

IMPEL Course Recommendation System

Selim Umit, Jason Kumar, Daniel Cone, Christian Etherton

Northeastern University

College of Engineering

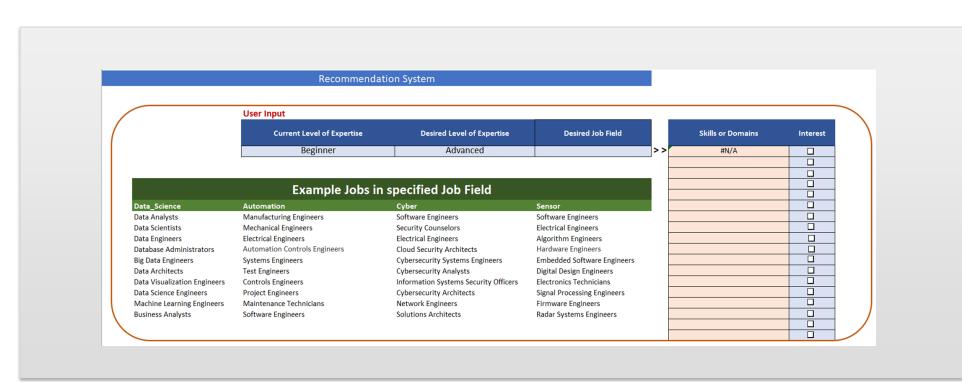
Results

Everything on the top half is the front-end with which the user sees and interacts. The bottom half is the back-end where everything is processed.

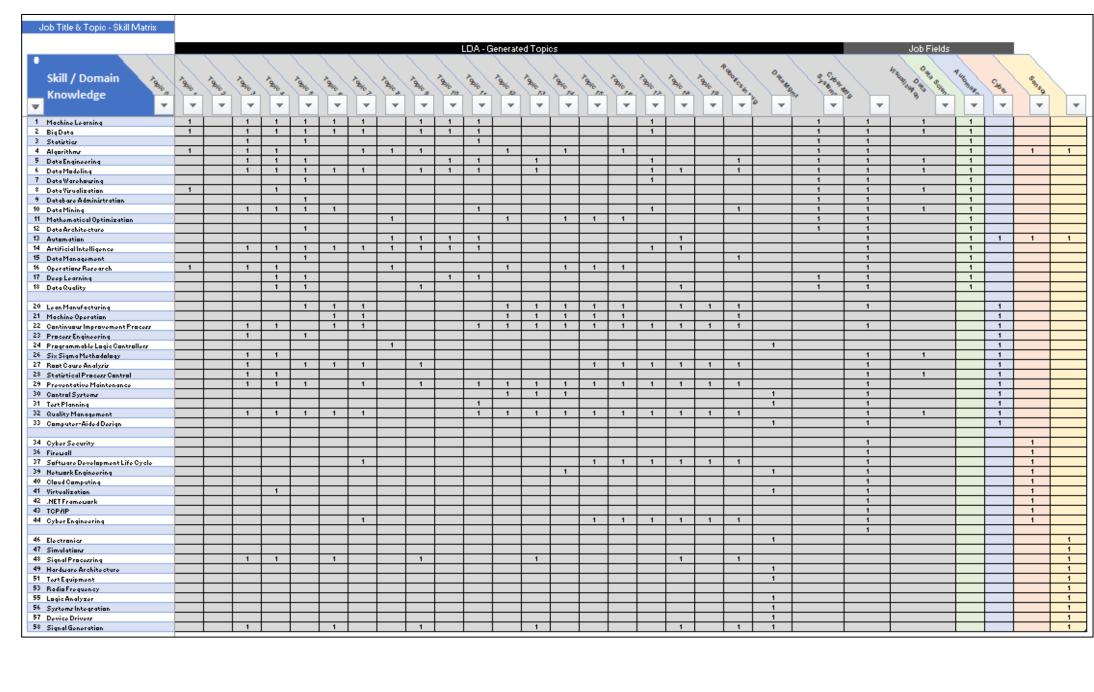
Red outlined steps are user inputs while green outlined steps represent the system output. Steps in yellow are back-end matrices and operations.

The user begins by identifying their expertise, the expertise needed for the jobs they desire, and their desired job field. The desired job field reveals related skills or knowledge domains from which the user can choose. This is based on the first backend matrix which connects the job field to skills.

After selecting the skills or knowledge domain most aligned with their desired jobs, the system maps their choices through two matrices that connect skills to algorithmically-grouped topics which then connects to the actual course modules. The grouping of these modules is the system output.



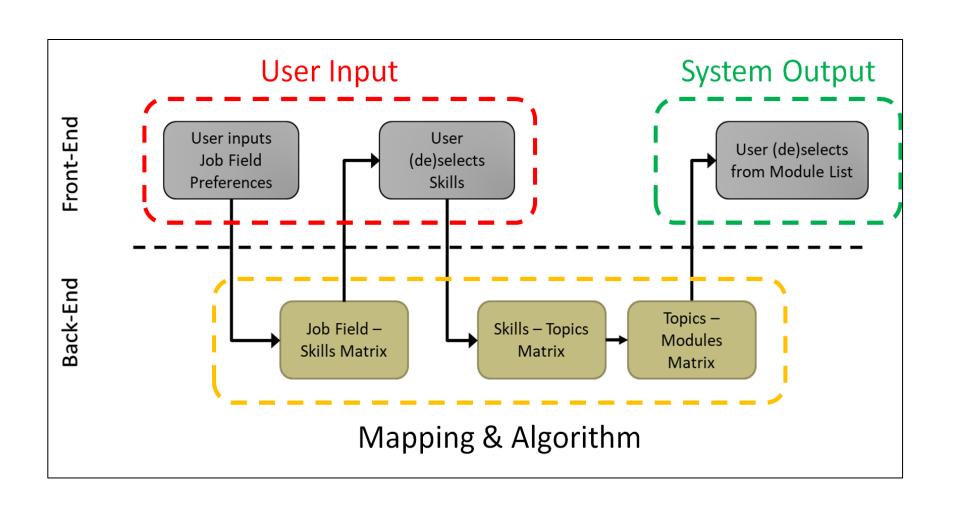
Job Field-Skills & Skills-Topic Matrices



Output

The recommendation systems output provides a table with all available courses. Courses which are not highly correlated are still present, so the user has the option to view other courses that might grab their interest. For the courses that are recommended the system blues and bolds them making them stand out and ensuring it is easy for the user to see. For the users who are seeking only the beginner courses, the user can toggle output between seeing both advanced and beginner courses or just beginner courses.

The output is simple and easy to understand, like the required input, making it easy on the user to use the system without running into any problems. The system is directly connected to the databases meaning that the system output is instantaneous. This simplifies the process it takes to guide users to their ideal course plan.



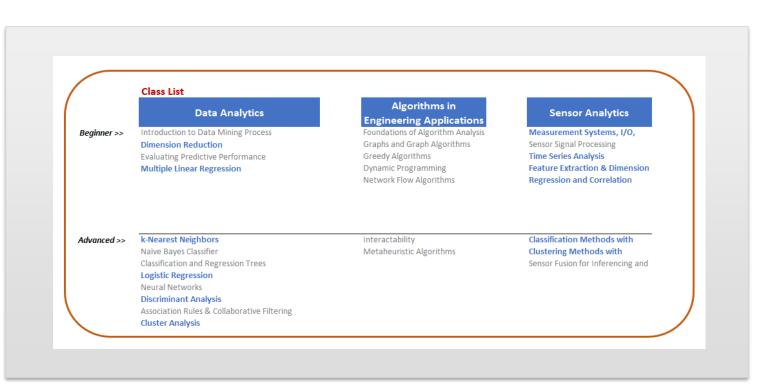
An interface that requires users to select their current level of expertise and then select their desired levels of expertise was chosen for the design. Following these selections, the user must select between the four job fields. In the U.I., the top ten most common jobs associated with each job field are included to help the user select whichever is most appropriate for them.

The desired job field selection uses the Job Field-Skills matrix to draw all the skills/domains associated with that specific job field. There is then a list of these skills/domains provided to the user, as seen to the left.

The Skills-Topic matrix uses values provided by subject matter experts to relate each skill/domain to a topic.

Topic-Module Matrix

	Topic-Module Matrix																				
											Тор	ice									
#	Module Name	DEO 1	and To	063 T	ook 3	got 15	065	Opic s	and I	DE 3	060 9	06 10 9	86 m	8 3 ×	8 3 8	36 Z 9	36 to 3	06 to 02	8 1 8	8 2 X	620
1	Overview of the Data Mining Process	0.003	0.077	0.047	0.025	0.495	0.006		0.005	0.015	0.018	0.018	0.014	0.011	0.008	0.046	0.002	0.103	0.005	0.026	0.066
2	Basic Data Visualization	0.014	0.042	0.018	0.617	0.069	0.035	0.011	0.012	0.006	0.006	0.022	0.007	0.032	0.005	0.011	0.009	0.012	0.022	0.006	0.046
	Advanced Data Visualization	0.014	0.074	0.007	0.620	0.098	0.026	0.007	0.006	0.005	0.006	0.004	0.012	0.005	0.005	0.018	0.003	0.014	0.026	0.009	0.041
	Dimension Reduction	0.012	0.083	0.107	0.015	0.079	0.032	0.004	0.004	0.006	0.012	0.013	0.015	0.030	0.004	0.008	0.003	0.042	0.008	0.004	0.519
	Measures and Metrics for Performance Evaluation	0.002	0.069	0.126	0.009	0.049	0.004	0.004	0.003	0.004	0.020	0.476	0.003	0.007	0.003	0.011	0.003	0.186	0.005	0.011	0.005
	Predictive and Classification Performance Evaluation N	0.004	0.084	0.012	0.012	0.014	0.010	0.020	0.005	0.002	0.021	0.726	0.005	0.003	0.003	0.011	0.003	0.044	0.009	0.005	0.005
	Multiple Linear Regression	0.003	0.058	0.449	0.006	0.014	0.004	0.005	0.006	0.007	0.013	0.020	0.014	0.040	0.004	0.014	0.005	0.283	0.012	0.003	0.039
	k-Nearest Neighbors	0.005	0.088	0.280	0.035	0.093	0.035	0.021	0.004	0.005	0.017	0.147	0.021	0.005	0.006	0.008	0.004	0.056	0.008	0.016	0.085
	The Naive Bayes Classifier	0.006	0.104	0.039	0.007	0.050	0.007		0.005	0.005	0.553	0.044	0.026	0.035	0.010	0.014	0.012	0.052	0.007	0.007	0.013
	Classification Trees	0.003	0.126	0.022	0.005	0.044	0.011		0.005	0.007	0.081	0.047	0.005	0.006	0.006	0.023	0.005	0.042	0.005	0.007	0.006
	Advanced Topics In Classification and Regression Tree	$\overline{}$	0.061	0.055	0.007	0.018	0.007		0.005	0.003	0.018	0.039	0.004	0.008	0.017	0.015	0.003	0.376	0.005	0.004	0.017
	Logistic Regression	0.003	0.031	0.133	0.009	0.014	0.008		0.007	0.007	0.551	0.045	0.006	0.040	0.039	0.008	0.004	0.055	0.005	0.012	0.020
	Neural Nets	0.005	0.113	0.063	0.039	0.040	0.004		0.010	0.005	0.035	0.022	0.004	0.014	0.577	0.014	0.007	0.017	0.008	0.003	0.007
	Advanced Concepts of Neural Nets	0.007	0.126	0.013	0.006	0.031	0.003		0.007	0.005	0.038	0.008	0.007	0.036	0.374	0.036	0.005	0.260	0.013	0.007	0.008
	Discriminant Analysis	0.005	0.056	0.055	0.009	0.027	0.081		0.010	0.009	0.477	0.017	0.011	0.022	0.005	0.011	0.005	0.019	0.005	0.008	0.161
	Association Rules and Collaborative Filtering	0.002	0.148	0.014	0.009	0.056	0.023	_	0.011	0.016	0.007	0.007	0.011	0.009	0.009	0.013	0.005	0.017	0.007	0.614	0.019
	Cluster Analysis	0.003	0.124	0.016	0.029	0.014	0.631		0.002	0.006	0.006	0.005	0.008	0.008	0.004	0.053	0.003	0.025	0.004	0.010	0.036
	Time Series Analysis	0.003	0.122	0.058	0.019	0.012	0.005	0.002	0.003	0.014	0.010	0.005	0.004	0.030	0.002	0.034	0.006	0.052	0.611	0.002	0.007
	Measurement Systems, I/O, Physical Principles of Sens	0.005	0.077	0.006	0.004	0.011	0.023	0.008	0.007	0.730	0.006	0.029	0.004	0.015	0.018	0.016	0.007	0.007	0.014	0.005	0.008
	Sensor Signal Processing	0.007	0.146	0.007	0.020	0.006	0.006		0.006	0.615	0.009	0.005	0.006	0.010	0.005	0.039	0.003	0.004	0.080	0.006	0.015
	Feature Extraction & Dimension Reduction	0.003	0.109	0.016	0.007	0.013	0.004		0.006	0.012	0.071	0.008	0.008	0.048	0.005	0.034	0.004	0.005	0.020	0.006	0.615
	Regression and Correlation	0.008	0.117	0.013	0.011	0.003	0.003		0.006	0.011	0.005	0.005	0.004	0.749	0.005	0.005	0.004	0.015	0.012	0.003	0.018
23	Classification Methods with Application in Fault Diagno	0.004	0.099	0.084	0.011	0.157	0.041	_	0.006	0.007	0.047	0.036	0.006	0.043	0.226	0.047	0.003	0.027	0.012	0.011	0.024
	Clustering Methods with Applications in Process Monito	0.005	0.114	0.029	0.022	0.123	0.374		0.010	0.004	0.063	0.019	0.005	0.009	0.034	0.083	0.006	0.015	0.055	0.011	0.010
25	Foundations	0.025	0.091	0.014	0.007	0.021	0.010	0.034	0.022	0.015	0.009	0.010	0.064	0.012	0.011	0.589	0.010	0.013	0.018	0.016	0.007
26	Graph Graph	0.739	0.054	0.007	0.006	0.004	0.002	_	0.023	0.002	0.002	0.001	0.008	0.005	0.004	0.108	0.014	0.002	0.006	0.004	0.005
	Greedy algorithm	0.113	0.093	0.003	0.003	0.004	0.006		0.514	0.004	0.002	0.004	0.018	0.002	0.002	0.198	0.017	0.002	0.002	0.006	0.004
	B Dynamic programming	0.037	0.145	0.004	0.002	0.001	0.001		0.683	0.002	0.004	0.002	0.016	0.006	0.005	0.056	0.011	0.005	0.007	0.007	0.002
	Network Flow	0.142	0.114	0.003	0.003	0.003	0.004		0.027	0.003	0.002	0.005	0.035	0.006	0.003	0.092	0.540	0.005	0.005	0.002	0.002
	Computational Intractability	0.060	0.126	0.003	0.002	0.003	0.003	0.003	0.010	0.002	0.012	0.003	0.680	0.003	0.003	0.065	0.010	0.002	0.002	0.005	0.002
31	Metaheuristic Algorithm																				
		1.24	2.87	1.70	1.57	1.57	1.47	1.15	1.43	1.53	2.12	1.85	1.03	1.25	1.40	1.68	0.72	1.76	1.00	0.84	1.81
	1	74%	74%	74%	74%	74%	74%		74%	74%	74%	74%	74%	74%	74%	74%	74%	74%	74%	74%	74%
	2	14% 11%	15% 15%	28% 13%	62% 4%	16% 12%	37% 9%		51% 3%	61% 2%	55% 48%	48% 15%	6% 4%	5% 4%	37% 23%	20% 11%	2% 1%	28% 26%	8% 6%	3% 2%	52% 16%
	<u>4</u>	6%	13%	13%	4%	10%	8%			1%	8%	10%	3%	4%	4%	9%	12	19%	3%	2%	9%
	5	4%	13%	11%	3%	9%	4%	2%	2%	1%	7%	5%	2%	4%	3%	8%	1%	10%	2%	1%	7%
	6	3% 1%	13% 12%	8% 6%	2% 2%	8% 7%	3% 3%		1% 1%	1% 1%	6% 5%	5% 4%	2% 2%	4% 4%	2% 2%	7% 6%	1% 1%	6% 6%	2% 2%	1% 1%	5% 4%
	8 8	1%	12%	6%	2%	7% 6%	3%		1% 1%	1% 1%	5% 4%	4% 4%	12	4% 3%	1%	5%	1%	5%	2% 1%	1% 1%	4% 4%
	ě	1%	12%	6%	2%	5%	2%	1%	1%	1%	3%	3%	1%	3%	1%	5%	1%	5%	1%	1%	4%
	10	1%	11%	5%	1%	5%	2%	1%	1%	1%	2%	2%	1%	3%	1%	5%	1%	4%	1%	1%	2%





Conclusions

The recommendation system offers a unique way to select courses that can connect someone to their desired career path. This method is more accurate than a standard university course plans that are primarily modeled on a "one size fits all" approach.

Through results of the survey, changes were made to optimize the interface of the system. These changes helped make the U.I. more user friendly. With the hand-off to the IMPEL team including this system being integrated into Canvas, there is potential for this course recommendation system to be adopted by universities as a more efficient course selection system. With a more personalized approach to course selection, this would enable earlier course planning for students. This could reduce the anxiety of selecting courses upon arrival to University. With further funding and testing this system could expand to be used throughout the country.

Finally, and more importantly this system would reduce the volume of cookie cutter approaches to university course plans allowing students to plan for the career they want. This solution offers greater flexibility in degree plans and more classes relating to individuals' careers goals.

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For Further Information

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