

### Lahore University of Management Sciences CS5302/ EE519 - Speech and Language Processing with Generative AI

Spring 2024

#### **Course description**

Generative AI stands at the cutting edge of today's artificial intelligence landscape, ushering in a new paradigm where machines not only understand intricate data patterns but also autonomously produce them. This in-depth course ventures into the fascinating world of Generative AI, cultivating a deep understanding of its potential to adeptly create, communicate, and innovate across diverse data forms. Students will gain hands-on experience with some of today's most renowned models, adapting them to unique use-cases while engaging with a vast array of topics—from foundational theories and principles to design, hands-on implementation, and thorough analysis of these systems. By the course's end, participants will be equipped to transition into the industry with tangible skills and a robust portfolio, contribute meaningfully to academic discourse by augmenting existing research or pioneering novel concepts, or embark on personal projects with an enhanced perspective and expertise.

Course distribution		
Elective	This is a Graduate Level CS elective course to be cross-listed as an undergraduate elective course.	
Open for Student Category	Juniors, seniors, and graduates.	
Close for Student Category	Please see the prerequisites below.	

#### **Course prerequisites**

All students must have taken CS535/EE514 (Machine Learning)

Course Offering Details					
Credit Hours	3 hours				
Lecture(s)	Nbr of lec(s) per week	2	Duration	75 minutes	
Recitation/Lab (per week)	Nbr of lec(s) per week		Duration		
Tutorial (per week)	Nbr of lec(s) per week	1 (optional)	Duration	50 minutes	

Instructor	Agha Ali Raza
Room No.	SBASSE 9-G49A
Office Hours	TBA
Email	agha.ali.raza@lums.edu.pk
Telephone	8565
Secretary/TA	TBA
TA Office Hours	TBA
Course URL (if any)	None

#### Course Teaching Methodology (Please mention the following details in plain text)

- Lectures: In-person.
- TA Sessions: TAs will conduct asynchronous and synchronous sessions (in-person and online) to cover tutorials related to assignments.
- **Exams:** Exams will be conducted in person in pre-scheduled sessions.
- Quizzes: Quizzes will be conducted during announced class timings.
- Class discussions: There will be a slack channel for all discussions (general, assignments, quizzes, etc.)

#### PROGRAM EDUCATIONAL OBJECTIVES (PEOs)

PEO-01	Demonstrate excellence in the profession through in-depth knowledge and skills in the field of Computing.
PEO-02	Engage in continuous professional development and exhibit a quest for learning.
PEO-03	Show professional integrity and commitment to societal responsibilities.

#### **Course Objectives**

The goal of this course is to

- Be able to utilize foundation models and tune them in order to achieve a well-defined goal
- Understand the theory of the ideas behind, and the applications of modern generative systems including Large Language Models
- Get hands-on experience with the creation of Al-powered applications
- Gain a firm grip on expertly critiquing and analyzing the entire pipeline of a system

# CLO1: CLO2: CLO3: CLO3: CLO4: Dy the end of the course, students should be able to: Understand the foundations and core ideas of modern Machine Learning architectures and models Appreciate the scope of datasets and variety of training mechanisms Learn core ideas in creating applications using these models, including use-cases and practical details Understand the evolution of foundation models in terms of techniques, scale, working mechanisms etc.

CLO	CLO Statement	Bloom's Cognitive Level	PLOs/Graduate Attributes (Seoul Accord)
CLO1			
CLO <sub>2</sub>			
CLO3			
CLO4			

#### **Grading Breakup and Policy**

Assessment	Weight (%)	Related CLOs	ACM Recommended Disposition
Assignments	25%		
Quizzes	20%		
Paper Presentations	20%		
Project	25%		
Final Exam	10%		

Examination deta	Examination detail			
Midterm Exam	Yes/No: Duration: Exam Specifications:	No		
Final Exam	Yes/No: Duration: Exam Specifications:	Yes 2.5 – 3 hours In-person exam		

#### SSE Council on Equity and Belonging

In addition to LUMS resources, SSE's **Council on Belonging and Equity** is committed to devising ways to provide a safe, inclusive and respectful learning, living, and working environment for students, faculty and staff. To seek counsel related to any issues, please feel free to approach either a member of the council or email at <a href="mailto:cbe.sse@lums.edu.pk">cbe.sse@lums.edu.pk</a>.

#### **Mental Health Support at LUMS**

For matters relating to counseling, kindly email <a href="mailto:student.counselling@lums.edu.pk">student.counselling@lums.edu.pk</a>, or visit <a href="https://osa.lums.edu.pk/content/student-counselling-office">https://osa.lums.edu.pk/content/student-counselling-office</a> for more information. You are welcome to write to me or speak to me if you find that your mental health is impacting your ability to participate in the course. However, should you choose not to do so, please contact the Counseling Unit and speak to a counselor or speak to the OSA team and ask them to write to me so that any necessary accommodations can be made.

#### **Harassment Policy**

SSE, LUMS and particularly this class, is a harassment free zone. Harassment of any kind is unacceptable, whether it be sexual harassment, online harassment, bullying, coercion, stalking, verbal or physical abuse of any kind. Harassment is a very broad term; it includes both direct and indirect behavior, it may be physical or psychological in nature, it may be perpetrated online or offline, on campus and off campus. It may be one offense, or it may comprise of several incidents which together amount to sexual harassment. It may include overt requests for sexual favors but can also constitute verbal or written communication of a loaded nature. Further details of what may constitute harassment may be found in the LUMS Sexual Harassment Policy, which is available as part of the university code of conduct.

LUMS has a Sexual Harassment Policy and a Sexual Harassment Inquiry Committee (SHIC). Any member of the LUMS community can file a formal or informal complaint with the SHIC. If you are unsure about the process of filing a complaint, wish to discuss your options or have any questions, concerns, or complaints, please write to the Office of Accessibility and Inclusion (OAI, oai@lums.edu.pk) and SHIC (shic@lums.edu.pk) —both of them exist to help and support you and they will do their best to assist you in whatever way they can. You can find more details regarding the LUMS sexual harassment policy here.

To file a complaint, please write to <a href="mailto:harassment@lums.edu.pk">harassment@lums.edu.pk</a>.

#### Rights and Code of Conduct for Online Teaching

A misuse of online modes of communication is unacceptable. TAs and faculty will seek consent before the recording of live online lectures or tutorials. Please ensure if you do not wish to be recorded during a session to inform the faculty member in a timely manner. Please also ensure that you prioritize formal means of communication (email, LMS) over informal means to communicate with course staff.

Course	overview	Recommended	Related	ACM Comp
Week	Topics	Readings	CLOs	Knowledge Landscape
1.	Course Overview			
	A history for Machine Learning			
	What is NLP/NLU?			
	o The Boom for Language Technologies			
	o Examples of Applications			
	What is Generative AI?			
	o Generative AI for language			
	o Generative AI for speech			
	o Generative AI for vision			
	Opportunities of ML			
	o ML for social good, ML for Development (ML4D), Language			
	Technologies for Development (LT4D)			
	Basics of Natural Language Processing			
	Natural language (and human speech)			
	<ul> <li>Subdomains in NLP and their applications</li> </ul>			
	o Phonetics and phonology			
	o Morphology			
	o Syntax			
	o Semantics			
	o Discourse and pragmatics			
	<ul> <li>Introduction to Python and the Natural Language Toolkit (NLTK)</li> </ul>			
	o English and Urdu Corpus processing			
	Regular Expressions			
	Normalization and collation; Surface form and deep structure; types and			
	tokens; root, lexeme, lemma			
	<ul> <li>Word formation processes: Inflection, derivation, compounding,</li> </ul>			
	cliticization, reduplication			

Word and Sentence tokenization	
Stem, stemming, Information Retrieval	
Morphology and Morphological Processing	
Language, script and style	
String similarity and distance	
Vector similarity and distance measures	
o Euclidean distance	
o Manhattan distance	
o Chebyshev distance	
o Cosine similarity	
Other string similarity and distance measures	
o Jaccard Similarity	
o Jaro similarity	
Jaro-Winkler similarity	
o Edit distance	
■ Levenshtein distance	
■ Damerau–Levenshtein distance	
■ Longest common subsequence (LCS)	
■ Hamming distance	
o Phonetic similarity	
2. Speech and Language Processing NLP Review	
Notion of Sequence Modeling tasks     Levels of	
o Text and Speech analysis:	
Recurrent Neural Networks     phonetics,	
o Overall Architecture phonology,	
o The Hidden State morphology,	
o "Unrolling" a unit syntax,	
• LSTMs semantics,	
o Changes to the Architecture pragmatics,	
o Storing the "memory" in a cell discourse	
Machine Translation and Embeddings  All terms in class.	
o Setup for a Seq2Seq problem All terminology o Tokenization of NLP	
o Embeddings as vector representations	
o Encoder-Decoder framework From my NLP	
o Information bottleneck: passing on only one hidden state outline.	
o Improvements 2 lectures	
■ Passing all the hidden states	
■ The Attention Mechanism <u>The Unreasonable</u>	
<u>Effectiveness of</u>	
<u>RNNs</u>	
<u>Visualizing A Neural</u>	
Machine Translation	
Model  Attacking to All Years	
3. Attention and Transformers  • The Attention Mechanism in Machine Translation  • Need  Need	
The Attention Mechanism in Machine Translation     Self-Attention	
o Det Dreduct Attention	
Jay Alaminar's Tile	
The Transformer and its advantages	
o Highly Parallelizable	
o Contextualized Embeddings vs. Regular Embeddings Some Intuition on	
o Long-Term Dependencies  Attention and the	
Transformer Architecture in a nutshell     Transformer	
o Attention Is All You Need	
o The Encoder The Annotated	
o The Decoder and Masked Attention Transformer	
o Query, Key, Value from tokens	
The Transformer in equations     Positional Embeddings	

	o Projections to QKV	<u>Transformers from</u>
	<ul> <li>Self Attention as Dot Product Attention</li> </ul>	Scratch
		Scruceri
	o Role of Feedforward Layers	
	o Multi-Headed Self Attention	
4.	Pre-Training and Transfer Learning	The Illustrated BERT
4.		THE MUSTICE DENT
	<ul> <li>Pre-training objectives vs. downstream tasks</li> </ul>	
	<ul> <li>Masked Language Modeling as a pre-training objective</li> </ul>	The State of
	Transformer Case Studies	Transfer Learning in
	o BERT: Bidirectional Encoder Representations from Transformers	NLP
	■ Encoder-based Transformer	
	■ Generating Embeddings	Universal Language
	■ Scaling up BERT: S to XL	Model Fine-tuning
	o T5: Text-to-Text Transfer Transformer	for Text
	■ Encoder-Decoder Transformer	Classification
		Classification
	<ul><li>Translation capabilities</li></ul>	
		Exploring Transfer
	Louisaging are trained models	Learning with T5
	Leveraging pre-trained models	Learning with 15
	<ul> <li>Fine-tuning models for downstream tasks</li> </ul>	
	Prompt Engineering	BERT: Bidirectional
	o Simple Prompts	<u>Encoder</u>
	o Chain-Of-Thought	<u>Representations</u>
	o In-Context Learning	from Transformers
	o m context Learning	
		T5: Text-to-Text
		Transfer
		<u>Transformer</u>
5.	Instruction-Tuned Models	What We Know
_	Generative Pretrained Transformer (GPT)	About LLMs
	o GPT-3 Case Study	(Primer)
	o Training Cycle	
	■ Pretraining, Supervised Fine-Tuning, RLHF	State of GPT
	e · ·	<u>State of di i</u>
	■ State of GPT	
	<ul> <li>Instruction Tuning</li> </ul>	ChatGPT
	o Issue with Alignment	CHALGPT
	o Relation to Pre-training and Fine-tuning	InstructGPT
	<ul> <li>Case Study: InstructGPT, Codex</li> </ul>	<u></u>
	Proprietary vs. Open-Source LLMs	
		<u>Language Models</u>
	o Drawbacks of reliance on Proprietary Models	are Few-Shot
	<ul> <li>The boom with Open-Source LLMs</li> </ul>	
	Alpaca and LLaMA	<u>Learners (GPT-3)</u>
	·	
	o Mining datasets	LLama 2: Open
	o Scale of the models	·
	Comparisons to proprietary counterparts	Foundation and
	Compansons to proprietary counterparts	<u>Fine-Tuned Chat</u>
		Models
		<u>Jessu Mu -</u>
		Prompting
6.	Case Studies for Specialized LLMs	Gorilla: Large
0.	•	
	• Gorilla	Language Model
	<ul> <li>Finetuning a model to use APIs</li> </ul>	Connected with
	Mitigating Hallucinations	Massive APIs
		MIGSSIVE FILES
	o Document Retriever to make updates	
	Orca	Orca: Progressive
	o Imitation learning	Learning from
	<ul> <li>Imitating the reasoning process, not the style of LLMs</li> </ul>	Complex
	<ul> <li>Finetuning on explanation traces</li> </ul>	Explanation Traces
	• Goat	of GPT-4
		<u> </u>
	<ul> <li>Improving mathematical abilities of LLMs</li> </ul>	
	<ul> <li>Tokenization of numbers</li> </ul>	Goat: Fine-tuned
	o Simplistic synthetic datasets	LLaMA Outperforms
	Evaluation of LLMs	GPT-4 on Arithmetic
	o Perplexity	<u>Tasks</u>
	o BLEU	
	Hallucinations in LLMs	
		· · · · · · · · · · · · · · · · · · ·

7.	Fine-Tuning Paradigms I	LoRA: Low Rank
/•	Conventional Fine-Tuning	Adaptation of Large
	Making all parameters trainable	Language Models
	o Freezing parameters	<u> Language mouers</u>
	In-Context Learning	<u>Finetuning Large</u>
	Mimicking Gradient Descent	Language Models
	o Few-Shot vs. Zero-Shot performance	
	Parameter Efficient Fine-Tuning (PEFT)	Explaining the Key
	<ul> <li>Limitations of compute</li> </ul>	Concepts Behind
	<ul> <li>Scaling up models</li> </ul>	LoRA
	o PEFT vs. Conventional Fine-Tuning	
	Low Rank Adaptation (LoRA)	Parameter Efficient
	<ul> <li>Injecting randomly initialized parameters</li> </ul>	Fine-Tuning (blog)
	<ul> <li>Feasibility on lower-tier machines</li> </ul>	Title raining (blog)
	Quantization	M. 1.1= 1.1.
	<ul> <li>Varying the precision of parameters</li> </ul>	Model Training
	o 32-bit vs. 16-bit vs. 8-bit vs. 4-bit	<u>Anatomy</u>
	o Case Study: fp16 vs. bfloat16	
8.	Fine-Tuning Paradigms II	QLoRA: Efficient
	<ul> <li>Quantized Low Rank Adaptation (QLoRA)</li> </ul>	<u>Finetuning of</u>
	<ul> <li>An amalgamation of different techniques</li> </ul>	<u>Quantized LLMs</u>
	o NF4, Nested Quantization, Paging Optimizers	
	o Fine-Tuning 20B LLMs on free-tier cloud instances	QLoRA Is All You
	o Inference Scaling Laws	<u>Need</u>
	Data Quality Influences on Model Performance	<u>The False Promise of</u>
	o Mining methods	<u>Imitating</u>
	<ul><li>Bonafide vs. Synthetic Data</li></ul>	<u>Proprietary LLMs</u>
	The False Promise of Imitating Proprietary LLMs	
	Less Is More for Alignment (LIMA)	<u>Less Is More for</u>
	o Textbooks Are All You Need	Alignment (LIMA)
		Toythooks Are All
		Textbooks Are All
0	Systems with NLD	You Need
9.	Systems with NLP  • Designing a System	You Need  Building RAG-based
9.	Designing a System	You Need  Building RAG-based  LLM Applications for
9.	<ul><li>Designing a System</li><li>Using LLMs out of the box vs. Fine-Tuning</li></ul>	You Need  Building RAG-based
9.	<ul> <li>Designing a System</li> <li>Using LLMs out of the box vs. Fine-Tuning</li> <li>Creating a Pipeline</li> </ul>	You Need  Building RAG-based  LLM Applications for  Production
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9.	<ul> <li>Designing a System</li> <li>Using LLMs out of the box vs. Fine-Tuning</li> <li>Creating a Pipeline</li> <li>Deployment options</li> <li>Information Retrieval Mechanisms</li> </ul>	You Need  Building RAG-based LLM Applications for Production  Explaining Vector Databases in 3
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	<ul> <li>Designing a System         <ul> <li>Using LLMs out of the box vs. Fine-Tuning</li> <li>Creating a Pipeline</li> <li>Deployment options</li> </ul> </li> <li>Information Retrieval Mechanisms         <ul> <li>Utilization of External Knowledge</li> <li>Vector Stores and Vector Databases</li> <li>Semantic Search</li> <li>Retrieval Augmented Generation (RAG)</li> <li>Mitigating the Hallucination Issue</li> <li>Case Study: Retrofit Attribution Using Research and Revision (RARR) for Fact-checking with LLMs</li> </ul> </li> <li>Multilingual NLP         <ul> <li>Challenges in training on languages outside of English</li> <li>Lack of data</li> <li>Differences between languages</li> <li>Skewed language distributions in large datasets</li> </ul> </li> </ul>	You Need  Building RAG-based LLM Applications for Production  Explaining Vector Databases in 3 Levels of Difficulty  Patterns for Building LLM-based Systems and Products  Using BERT pre- trained Embeddings directly for Semantic Search How Multilingual is Multilingual BERT?
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	<ul> <li>Designing a System         <ul> <li>Using LLMs out of the box vs. Fine-Tuning</li> <li>Creating a Pipeline</li> <li>Deployment options</li> </ul> </li> <li>Information Retrieval Mechanisms         <ul> <li>Utilization of External Knowledge</li> <li>Vector Stores and Vector Databases</li> <li>Semantic Search</li> <li>Retrieval Augmented Generation (RAG)</li> <li>Mitigating the Hallucination Issue</li> <li>Case Study: Retrofit Attribution Using Research and Revision (RARR) for Fact-checking with LLMs</li> </ul> </li> <li>Multilingual NLP         <ul> <li>Challenges in training on languages outside of English</li> <li>Lack of data</li> <li>Differences between languages</li> <li>Skewed language distributions in large datasets</li> </ul> </li> <li>Multilingual BERT (mBERT)         <ul> <li>Dataset and mining techniques</li> </ul> </li> </ul>	You Need  Building RAG-based LLM Applications for Production  Explaining Vector Databases in 3 Levels of Difficulty  Patterns for Building LLM-based Systems and Products  Using BERT pre- trained Embeddings directly for Semantic Search How Multilingual is Multilingual BERT?  MuRIL: Multilingual Representations for Indian Languages
	Designing a System	You Need  Building RAG-based LLM Applications for Production  Explaining Vector Databases in 3 Levels of Difficulty  Patterns for Building LLM-based Systems and Products  Using BERT pre- trained Embeddings directly for Semantic Search How Multilingual is Multilingual BERT?  MuRIL: Multilingual Representations for Indian Languages  State of Multilingual
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		Multilingual
		Language Models
11.	Multimodal Models	Douwe Kiela -
• • • • • • • • • • • • • • • • • • • •	What are Multimodal Models?	Multimodal Deep
	Vision and Language	Learning
	Language and Speech	<u>=====================================</u>
	o Examples of tasks	Multimodal Machine
	■ Image Captioning	Learning CVPR 2022
	■ VQA	Tutorial (series)
	■ Zero-shot Image Classification	-atona (sones)
	Background Concepts	How Multimodal
	o Multimodal Fusion	Models are leading
	o Cross-modal Attention Mechanisms	the way
	Deep Learning for Computer Vision	
		Fundamentals of
	Multimodal Models for Vision and Language	Multimodal
	Vision-Language Pretraining	Representation
	o Contrastive Learning	Learning
	o Introduction to Contrastive Language-Image Pretraining (CLIP)	<u>=====================================</u>
12.	Multimodal Models II	Foundation Models -
	Contrastive Language-Image Pretraining (CLIP)	CLIP
	o Architecture	
	Training Mechanism	Learning
	LLaVA: Large Language and Vision Assistant	Transferable Visual
	Applications	Models from Natural
	Visual Question Answering	Language
	Optical Character Recognition	Supervision
	Action Recognition from Video	
	Object Classification	The Annotated CLIP
	,	(Part 1, Part 2)
		,,
		<u>LLaVA Webpage</u>
		<u>Visual Instruction</u>
		<u>Tuning</u>
13	Explainability	What is Explainable
	The importance of Explainable AI (XAI)	<u>AI?</u>
	<ul> <li>Motivation and the need for explainability</li> </ul>	
	<ul> <li>Intrinsic vs. Post-hoc Explainability</li> </ul>	<u>Introduction to</u>
	<ul> <li>Intrinsic Explainability in model design</li> </ul>	Explainable AI (ML
	<ul> <li>Post-hoc techniques for existing models</li> </ul>	<u>Tech Talks</u> )
	Visualization techniques	
	<ul> <li>Heatmaps for feature importances</li> </ul>	
	Attention maps to understand relations	
14	Ethics	Word Embeddings,
•	Cases of Misuse	Bias in ML, Why You
	Misinformation and its impact	Don't Like Math &
	Creation and detection of fake news	Why Al Needs You
	Legal and Ethical implications	
	o Media literacy	21 Definitions of
	Bias and Fairness	<u>Fairness</u>
	o Algorithmic bias	Havy Algorithma Com
	o Building systems with ethical considerations	How Algorithms Can
	Privacy and Surveillance     Privacy and Surveillance	Learn to Discredit
	o Implications for Cybersecurity	"the Media"
	o GDPR and the "right to explanation"	The Problem with
	o Countermeasures	The Problem with
		<u>Metrics</u>
	Other topics – to be covered if we have tim	le

#### Textbook(s)/Supplementary Readings

Speech and Language Processing by Jurafsky and Martin, 3rd edition

#### Course policies

**Use of electronic devices (e.g., mobile phones and laptops) in the class is strictly forbidden.** A violation could result in deduction of marks and other strict penalties

Late arrival: You may not be allowed in the class 10 minutes after the start time

**Plagiarism:** All work MUST be done independently. In certain assignments students will be allowed to have discussions with peers, in which case they must mention the name and roll number of the student with whom the discussion took place and the nature of the discussion. Even in those assignments, all implementations need to be done independently. Any plagiarism or cheating of work from others or the internet will be immediately referred to the DC. If you are confused about what constitutes plagiarism, it is YOUR responsibility to consult with the instructor or the TA in a timely manner. No "after the fact" negotiations will be possible.

Submitting someone else's assignment as your own "by mistake" would count as plagiarism. If this indeed happens accidentally, please
let us know immediately (within minutes) along with an explanation and do not wait until we find it out on our own. In the latter case,
it would be considered plagiarism.

**Quizzes:** Quizzes will be unannounced. We will be following an n-x (x=2) policy for the quizzes. There is no makeup for a missed quiz. If you have missed up to x quizzes, you will be covered only using the n-x policy (even if you have an approved petition with the OSA). If you have missed more than x quizzes, then you would be awarded the average marks (across all the quizzes that you attempted) for each missed quiz, provided that your case has been approved by the Office of Student Affairs.

**Non-uniform weightage:** All subcomponents (e.g., quizzes, assignments) may not carry the same weight. These weights may not be announced prior to the submission of the components and will be determined by the course instructor based on factors including (but not limited to) the length, difficulty level, amount of help available, etc. for each subcomponent.

**Programming:** Strong programming skills are expected for this course. Please keep in mind that this is a programming intensive course, and you will be spending a lot of time designing and coding up your solutions.

**Assignments:** There is negative marking for skipped assignments and there is no n-x policy for assignments. Assignments are a basic building block of this course, and it will be ensured that students, who pass the course, have significant hands-on experience.

- You will be awarded o marks or investigated for plagiarism for submitting incorrect/corrupted files and/or older assignments. We will not accept resubmissions in these cases even if the system date shows that the file was not modified after the deadline.
- You are allowed 5 grace days for the entire semester. No late submission of assignments is allowed after your grace days have expired. We do not have any deduction policy for late submissions in addition to the grace days. All grace days must be utilized before the start of the dead week and any remaining grace days will expire as soon as the dead week begins.
- Please do not wait until the last moment to submit assignments and other components. Any requests to accommodate late submissions due to last minute issues (submission of partial or incorrect files, assignment server down-time, internet and power failures, personal problems, etc.) would not be accommodated.

#### Appendix A Bloom's Taxonomy

# BLOOM's TAXONOMY\* 1 - Remember 2 - Understand 3 - Apply 4 - Analyze 5 - Evaluate 6 - Create • Recall facts and basic concepts • Explain ideas or concepts • Use information in new situations • Draw connection among ideas • Justify a stand or decision • Produce new or original work

https://cft.vanderbilt.edu/guides-sub-pages/blooms-taxonomy/

#### Appendix B

#### ACM Dispositions Table - I

ACM Dispositions							
Element	Elaboration	Element	Elaboration				
D1 Adaptable:	Flexible; agile, adjust in response to change	D7 Professional:	Professionalism, discretion, ethical, astute				
D2 Collaborative:	Team player; willing to work with others	D8 Purpose- driven:	Goal driven, achieve goals, business acumen				
D <sub>3</sub> Inventive:	Exploratory; Look beyond simple solutions	driveri:	Use judgment, discretion, act appropriately				
D4 Meticulous:	Attentive to detail; thoroughness, accurate	D9 Responsible:	Respectful; react quickly and positively				
D5 Passionate:	Conviction, strong commitment, compelling	D10 Responsive:	Self-motivated, determination, independent				
D6 Proactive:	With initiative, self-starter, independent	D11 Self-directed:					

#### **ACM Dispositions Table - II**

Class Assessments and Proposed Dispositions												
Assessment Type	D1 Adaptable	D2 Collaborativ e	D <sub>3</sub> Inventive	D4 Meticulous	D <sub>5</sub> Passionate	D6 Proactiv e	D <sub>7</sub> Professiona I	D8 Purpose- driven	D9 Responsibl e	D10 Responsiv e	D11 Self- directed	Included
Quiz				✓			✓		✓			Yes
Assignment- Individual			✓	✓			✓		✓			Yes
Assignment- Group		✓	✓	✓			✓		✓	✓		Yes
Project- Individual	✓		✓	✓	✓	<b>√</b>	✓	✓	✓		✓	Yes
Project- Group	1	✓	✓	✓	<b>√</b>	✓	✓	<b>√</b>	√			Yes
Presentation - Individual				✓			✓		✓	✓	✓	Yes
Presentation - Group		✓		✓			✓		✓	✓		Yes
Labs- Individual			✓	✓			✓		✓			Yes
Labs- Group		✓	✓	✓			✓		✓	✓		Yes
Exams				✓			✓		✓			Yes
Included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	

## Appendix C ACM Computing Knowledge Landscape Table

ACM Computing Knowle	edge Landscape (CK)		
1. Users and Organizations	CK1.1: Social Issues and Professional Practice CK1.2: Security Policy and Management CK1.3: IS Management and Leadership CK1.4: Enterprise Architecture CK1.5: Project Management CK1.6: User Experience Design	4. Software Development	CK4.1: Software Quality, Verification and Validation CK4.2: Software Process CK4.3: Software Modeling and Analysis CK4.4: Software Design CK4.5: Platform-Based Development
2. Systems Modeling	CK2.1: Security Issues and Principles CK2.2: Systems Analysis & Design CK2.3: Requirements Analysis and Specification CK2.4: Data and Information Management	5. Software Fundamentals	CK5.1: Graphics and Visualization CK5.2: Operating Systems CK5.3: Data Structures, Algorithms and Complexity CK5.4: Programming Languages CK5.5: Programming Fundamentals CK5.6: Computing Systems Fundamentals
3. Systems Architecture and Infrastructure	CK3.1: Virtual Systems and Services  CK3.2: Intelligent Systems (AI)  CK3.3: Internet of Things  CK3.4: Parallel and Distributed Computing  CK3.5: Computer Networks	6. Hardware	CK6.1: Architecture and Organization CK6.2: Digital Design CK6.3: Circuits and Electronics CK6.4: Signal Processing