# **Course Change Request**

# **New Course Proposal**

Date Submitted: 04/17/24 2:51 pm

# Viewing: CSS 717 : Verification and Validation of

# **Models**

Last edit: 04/17/24 2:51 pm

Changes proposed by: blaisten

Are you completing this form on someone else's behalf?

# In Workflow

- 1. CDS Chair
- 2. SC Curriculum Committee
- 3. SC Assistant Dean
- 4. Assoc Provost-Graduate
- 5. Registrar-Courses
- 6. Banner

# **Approval Path**

1. 04/17/24 3:16 pm Jason Kinser (jkinser): Approved for CDS Chair

Yes

#### **Requestor:**

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Nam	ie	Extension	Email
Estela Blaisten		31988	blaisten@gmu.edu
Effective Term:	Summer 2025		
Subject Code:	CSS - Computa	tional Social Science	Course Number: 717
Bundled Courses:			
Is this course replaci	ng another cours	se? No	
Equivalent Courses:			
Catalog Title:	Verification an	d Validation of Models	
Banner Title:	Verificatn Valio	datn of Models	
Will section titles vary by semester?	No		
Credits:	3		
Schedule Type:	Lecture		

4/17/24, 5:31 PM			CSS 717: Verificati	on and Validatio	n of Models
Hours of Lecture or Se week:	minar per	3			
Repeatable:	May only be taken *GRADUATE ONLY	once fo *	or credit (NR)		
Default Grade Mode:	Graduate Regular				
Recommended Prerequisite(s): CSS 600, CSS 605, CSS Recommended Corequisite(s):	S 610, or CSS 692; o	or the pe	ermission of th	ne instructor	r.
Required Prerequisite(s) / Corequisite(s) (Updates only):					

#### **Registrar's Office Use Only - Required Prerequisite(s)/Corequisite(s):**

And/Or	(	Course/Test Code	Min Grade/Score	Academic Level	)	Concurrency?

Registration Restrictions (Updates only):

**Registrar's Office Use Only - Registration Restrictions:** 

Field(s) of Study:

Class(es):

Level(s):

Degree(s):

School(s):

## Catalog

## Description:

This course covers verification and validation (V&V) practices across different modeling techniques. Topics include V&V terminology, data visualization for V&V, runtime verification, validation of machine learning, agent-based, cognitive, statistical, and network models as well as ethics of model development and use.

## Justification:

#### CSS 717: Verification and Validation of Models

What: Computational-based models come in different forms ranging from machine learning models that predict/classify patterns to agent-based models that investigate emergent phenomena from a bottom-up perspective. This course covers a wide range of verification and validation (V&V) practices in computational model development.

Why: All computational models should go through a verification and validation process, which checks the correctness of the model design and implementation as well as its performance. This course will teach and improve computational model verification and validation, which is considered an essential methodological step in computational model development. Overall, knowledge gained from this class will lead to robust research practices for students who develop computational models.

# Does this course cover material which No crosses into another department?

## Learning Outcomes:

--Analyze principles governing verification and validation for different types of computational models.

--Evaluate ethical implications of model use in the real world.

--Apply the main principles of verification and validation for analyzing the quality of a variety of scientific models.

--Create and evaluate computational models from the perspective of V&V.

Will this course be scheduled as a cross- No level cross listed section?

## Attach Syllabus CSS-717 Syllabus April10 2024.pdf

Additional Attachments

## Staffing:

Dr. Hamdi Kavak, Assistant professor, Department of Computational and Data Sciences. Other possible instructors: Dr. William G Kennedy, Dr. Anamaria Berea.

# Relationship to

# **Existing Programs:**

This course is mainly tailored to the Computational Social Science, PhD students and will be of interest for students in the Computational Science and Informatics, PhD, and the Computational Science MS programs.

# Relationship to

# Existing Courses:

The course will complement the knowledge students acquire in CSS 600 Introduction to Computational Social Science, CSS 610 Agent-based Modeling and Simulation, and CSS 692 Social Network Analysis.

# Additional

## **Comments:**

The course will be added in the catalog to the list of Extended Core Courses of the CSS, PhD program (banner code SC-PHD-CSS).

4/17/24, 5:31 PM

Reviewer Comments

Key: 18665

# **CSS-717: Verification and Validation of Models**

#### 1. General Information

Instructor:	Dr. Hamdi Kavak ( <u>hkavak@gmu.edu</u> )
Department:	Computational and Data Sciences
Time, location, website:	TBD
Credits:	3
Prerequisites:	CSS 600, CSS 605, CSS 610, or CSS 692; or the permission of the instructor.

#### 2. Course Description

Computational models come in different forms, ranging from machine learning models that predict/classify patterns to agent-based models that investigate emergent phenomena from a bottom-up perspective. Regardless of their form, all computational models should go through a verification and validation (V&V) process, which checks the correctness of the model design and implementation as well as its success. Currently, V&V is considered an essential methodological step in computational model development and application. The proliferation of high-level frameworks and computational tools has enabled the possibility of bypassing or overlooking such crucial steps. This course aim is to teach V&V and instill in students a set of proficient V&V practices. Topics include terminology and history of V&V, statistics and visualization for V&V, runtime verification, validation of machine learning models, validation of statistical models, and validation in the absence of data, among many others. Students will further their knowledge with short writing assignments, paper presentations, and the final project.

#### 3. Learning Outcomes

By the end of the course, students will

- have proficiency on the principles of verification and validation for different types of computational models,
- be able to assess the ethical implications of using models in the real world,
- apply the main principles of verification and validation to analyze the quality of a variety of scientific models,
- create and evaluate computational models with respect to verification and validation.

#### 4. Textbooks and Other Instructional Material

The list of books recommended (not required) for this course is as follows:

- Verification and Validation in Scientific Computing by William L. Oberkampf. Publisher: Cambridge University Press, 2010.
- The MITRE Systems Engineering Guide. <u>https://www.mitre.org/sites/default/files/publications/se-guide-book-interactive.pdf</u>
- Modeling and Simulation Fundamentals: Theoretical Underpinnings and Practical Domains by John A. Sokolowski and Catherine M. Banks. Publisher: Wiley, 2010.

#### 5. IT Requirements

Students are required to have regular, reliable access to a computer with an updated operating system and a stable broadband Internet connection.

#### 6. Grades

Final grades at the end of the course will be assigned based on the following table, independent of the relative standing in the class.

Short writing assignment (SWA)	20 pts
Paper presentation	30 pts
Final project	<b>50 pts</b> (10% proposal,
	20% presentation,
	70% paper)

Final Mark	Corresponding Grade
>=97	A+
93.0 – 96.99	А
90.0 - 92.99	A-
87.0 – 89.99	B+
83.0 - 86.99	В
80.0 - 82.99	В-
70.0 – 79.99	С
< 70.0	F

#### 7. Weekly Course Outline

1	Introduction and Models in Science: Motivation and learning objectives, semester topics list,
	grading, and the final project description. Description of models in science, explanation of why
	researchers develop models, aspects of models, and the boundaries of model correctness.
2	Verification and Validation Fundamentals: Basics of models verification and validation (V&V),
	terminology employed in domain, such as modeling and simulation, software engineering, and
	systems engineering. Time evolution of simulation verification. The V&V role in various model
	development processes and life cycles. Introduction to V&V different techniques.
3	Statistical and Visualization Techniques for V&V: Statistics and visualization concepts for model V&V,
	random variables, random number generators, uncertainty and confidence intervals, significance
	and similarity tests, boxplots, Q-Q, P-P plots.
4	Runtime Verification: Historical background on Runtime Verification (RV) in modeling and
	simulation, description of lightweight feedback-driven runtime verification (LFV) for addressing
	existing shortcoming. Hands-on examples using the LFV for Discrete Event Simulations using the
-	CLOUDES platform.
5	<u>Computational Techniques to Support Simulation Model Validation</u> : Algorithmic or heuristic
	techniques for increasing confidence in models: (1) warm-up periods and steady-state simulation,
	(2) Calibration and parameter estimation with hands-on demo, and (5) sensitivity analysis and
6	Sampling.
Ŭ	interactions between people things places and time ABMs are based on individual agents that are
	assigned attributes and rules, which comes with challenges related to V&V. Both, common practices
	and recent V&V techniques are discussed.
7	V&V within Cognitive Modeling of Individuals: Practices of V&V in Cognitive Modeling within
	Cognitive Science. Description of a cognitive phenomenon and a possible cognitive model. Cognitive
	modeling in relation to Artificial Intelligence. Cognitive architectures and lines of reasoning.
	Application of V&V to the ACT-R cognitive architecture. A specific cognitive model of intuitive
	learning.
8	Safer Deep Reinforcement Learning: Safe reinforcement learning is an open research subject.
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#### 8. General University Policies

The course abides by all the Mason policies. AN important set of them are listed below. For distribution to students and extramural posting, the syllabus will contain the requirement of including Mason's policies as described in: <u>https://stearnscenter.gmu.edu/knowledge-center/designing-your-syllabus/</u>

<u>Mason Honor Code</u> (quote from catalog.gmu.edu): "To promote a stronger sense of mutual responsibility, respect, trust, and fairness among all members of the George Mason University community and with the desire for greater academic and personal achievement, we, the student members of the university community, have set forth this honor code: Student members of the George Mason University community pledge not to cheat, plagiarize, steal, or lie in matters related to academic work."

<u>Email policy</u>: Mason's electronic mail provides any official information to students. Any class materials, assignments, questions, and instructor feedback should use the email Mason email. Students are responsible for maintaining their email account active, working correctly, and should check their content regularly (review details in catalog.gmu.edu).

<u>Plagiarism policy for Internet materials</u>: Copyright rules apply to users of the Internet who employ elements downloaded from Internet sources. Any information in the form of graphics, text, tables, or data accessed electronically and used in homework, presentations, exams, email, reports, must be cited giving credit to the pertaining sources. Even if credit is given, students must obtain permission from any copyrighted source to use any material not created by them. Inserting someone's else material in your work is stealing intellectual property. Including a link to the site URL is currently an appropriate citation.

<u>Student privacy policy</u>: Mason complies with FERPA by protecting the privacy of student records and judiciously evaluating requests for release of information from those records. It is not permitted for faculty to share class progress or grade information with parents/guardians under any circumstances. Student privacy policy: https://registrar.gmu.edu/students/privacy/

<u>Academic integrity</u>: This course embodies the value that we all have differing perspectives and ideas, and we each deserve the opportunity to share our thoughts. Therefore, we will conduct our discussions with respect for those differences. That means, we each have the freedom to express our ideas, but we should also do so keeping in mind that our colleagues deserve to hear differing thoughts in a respectful manner, i.e. we may disagree without being disagreeable. https://oai.gmu.edu/

<u>Students with disabilities:</u> Students with disabilities should contact the Office of Disability Services (ODS). Students requiring special accommodations should inform the instructor the first week of classes. Accommodations may be appropriate for situations that directly affect the student academic performance. ODS requires pertinent medical documentation of a physical, mental health, attention, or other health challenge. https://ds.gmu.edu/.