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EXPLORING ANALOGICAL REASONING CAPABILITIES WITHIN A COGNITIVE MODEL

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Motivation for Model of Analogical Reasoning

- Intelligent Cognitive Agent Research
 - Deal with incomplete knowledge
 - "Understanding", knowledge transfer, and generalization
- Technical Questions
 - Build/refine representations?
 - Determine similarity: words, relations, analogs?
 - Scalability and constraints
- Theoretical Questions
 - Representing analogs/systems?
 - Similarity, analogical distance, and relation hierarchies?
 - Exhaustive, partial, or heuristic processes?

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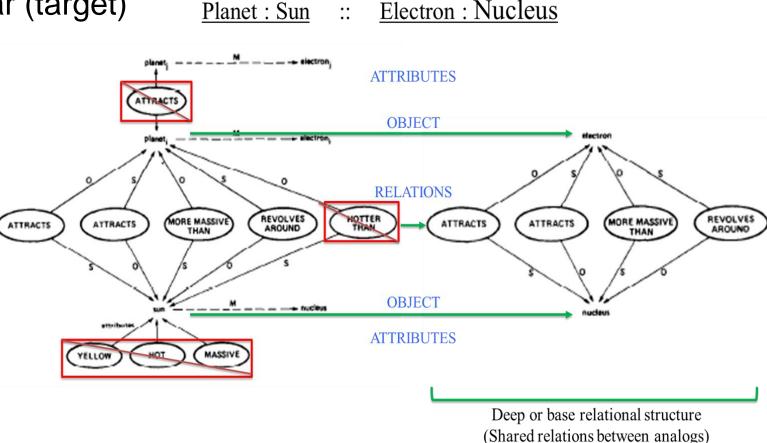
ANALOGICAL REASONING THEORY

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Analogical Reasoning – What is it?

- Relational system and infer new information (Gentner & Smith, 2013)
- Familiar (source) -> less familiar (target)
- Structure mapping (Gentner, 1983)
 - Situations are systems
 - Objects, attributes, and relations
 - Levels of mapping
 - Literal/surface similarity
 - Abstraction
 - Analogy



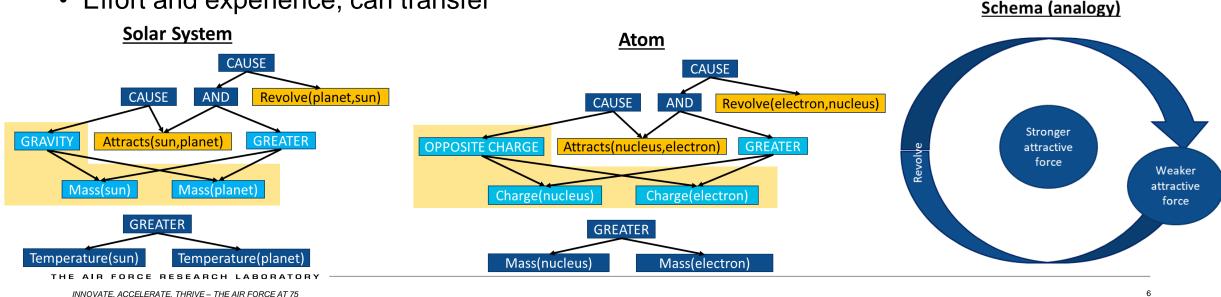




Analogical Reasoning – What is it?

Schemas and transfer in problem solving (Gick & Holyoak, 1983)

- Analogy partial mapping and extension of attributes/relations
 - Not always noticed, include surface and deep structure
- Schema deep structure/relations
 - Effort and experience, can transfer







MODELING ANALOGICAL REASONING

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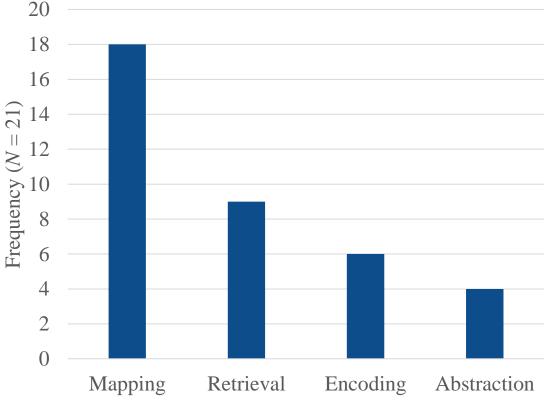


Modeling Analogical Reasoning

Core Features (Gentner & Forbus, 2011)

- Mapping
 - Types (Forbus et al., 2017)
 - Constraints
- Retrieval
 - Separate from mapping?
- Encoding/representation
 - Hard coding and other processes
 - Mapping and representation
- Abstraction/generalization
 - Schemas and anti-unification

Common Model Features (Gentner & Forbus, 2011)





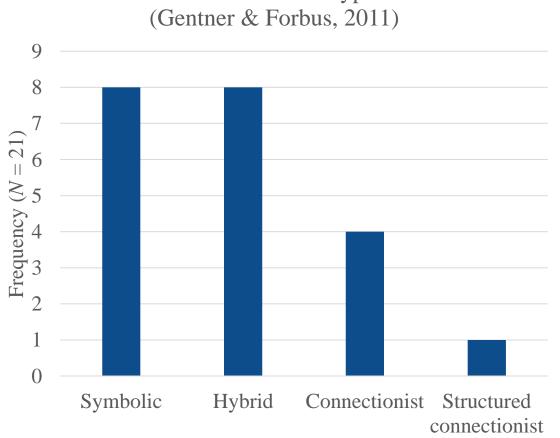
Modeling Analogical Reasoning

Model Types (Gentner & Forbus, 2011)

- Connectionist (ACME, ARCS, CAB, DORA)
- Structured Connectionist (LISA)
- **Symbolic** (CARL, HDTP, IAM, NLAG, **SME**, **MAC/FAC**, **SEQL**, SOAR, Winston)
- **Hybrid** (**ACT-R**, AMBR, **Companions CA**, CopyCat, DUAL, EMMA, TableTop)

Challenges (Genter & Forbus, 2011; Forbus et al., 2017)

- Appropriate representations
- Hard/hand coding and databases
- Interleaving cognitive processes
- · Applying to cognitive phenomena
- Cognitive plausibility



Common Model Types





EXAMPLE MODELS

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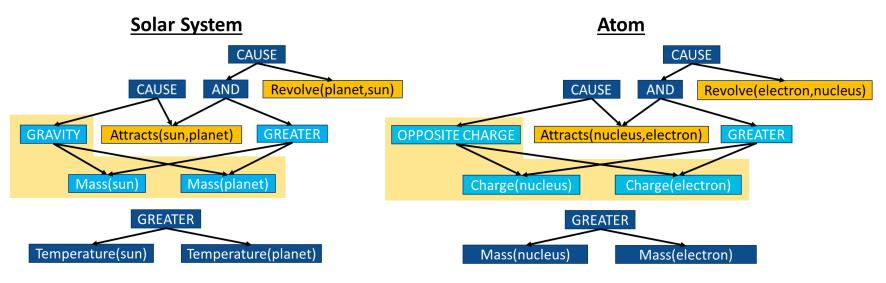
Example Models – Structure Mapping Engine

SME - Structure Mapping Engine (Falkenhainer et al., 1989; Forbus et al., 2017)

- Component used in larger systems
- Similarity and extrapolation (candidate inferences)
- Finds deep structure to compare systems (analogs)
 - Greater force(gravity/charge) → attraction → revolve
- Used in:



- SEQL (Kuehne et al., 2000)
- Companions architecture (Blass & Forbus, 2017; Forbus et al., 2009; Ribeiro & Forbus, 2021)





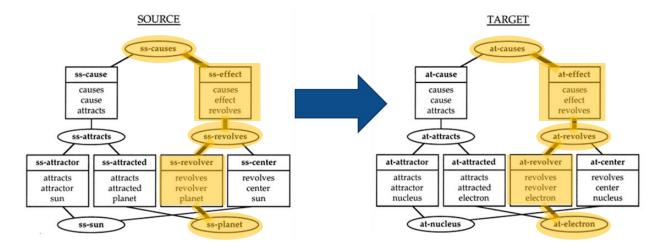
Example Models – Path Mapping Model

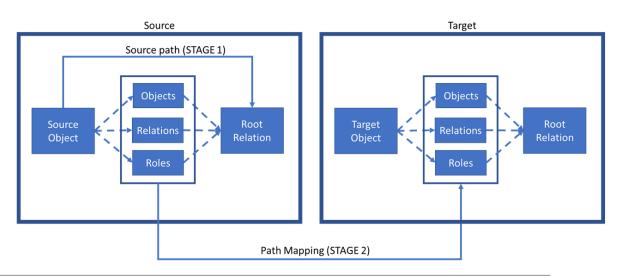
ACT-R – path mapping theory

(Salvucci & Anderson, 2001)

AFR

- Representation
 - Decomposed into chunks with objects, relations, and roles
- Path Mapping
 - Domain general set of rules to map object in source to one in target
- Organization (encoding)
 - When/how to use path mapping for specific tasks





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CAN WE OVERCOME CHALLENGES?

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Can We Overcome Challenges

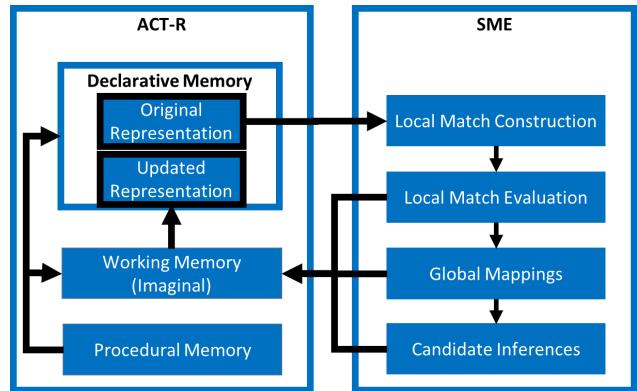
- Desired Capabilities
 - Take input and appropriately represent
 - Determine word and relation similarity/meaning
 - Structure alignment/mapping
 - Cognitive plausibility
 - Interleave cognitive processes
 - Apply to different high-level cognitive phenomena
- An exploration...
 - Leveraging ACT-R and SME
 - Get cognitive plausibility for free with ACT-R
 - Remaining 3 require some hard coding





Overcoming Challenges – Proof of Concept Model

- •Refine knowledge with analogical processes
- •SME as external ACT-R module
- •Given base \rightarrow find best matching target
 - •Retrieve chunks for system
 - •Compile into file (abstract representation)
 - •Use SME to compare two systems
 - •Leverage SME output to update
- Desired capabilities from SME
 - •Relation/structural similarity and extrapolation





Overcoming Challenges – Proof of Concept Model

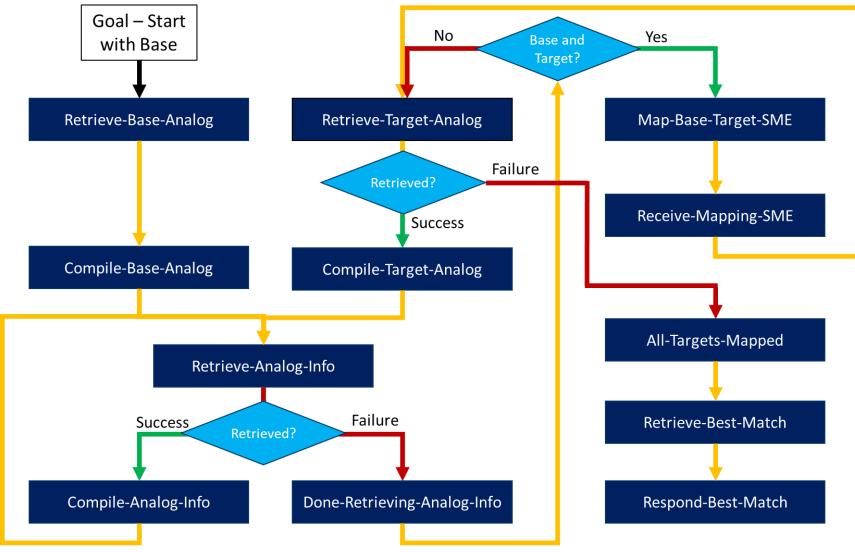
- Knowledge of systems or analogs
 - Define system solar-system contains sun and planet (objects)
 - Define attribute(s) **solar-system** object **sun** has property **hot**
 - Define relation(s) solar-system has relation gravity where sun is greater-than planet
 - Causality chains? mass causes gravity, gravity causes attraction, attraction causes revolving
 - New or existing chunk?

Ss-mass-gravity	isa	relation
System		SS
Туре		effect
Role-E1		causes
Entity1		mass
Entity2		gravity





Overcoming Challenges – Proof of Concept Model

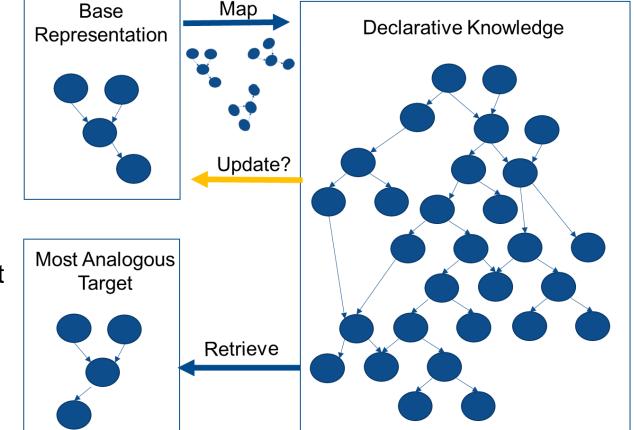


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Overcoming Challenges – What We Still Need

- Proof of Concept Model
 - Cognitive plausibility challenges
 - Knowledge of what and how
 - Cognitive flexibility
- Challenges not addressed
 - Knowledge Representation
 - Method to leverage complete SME output
 - Efficient search with constraints
- Questions remain







SPECIAL THANKS TO: Chris Myers Christian Lebiere Leslie Blaha

QUESTIONS?

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EXTRASLIDES

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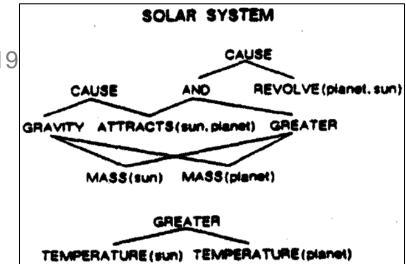


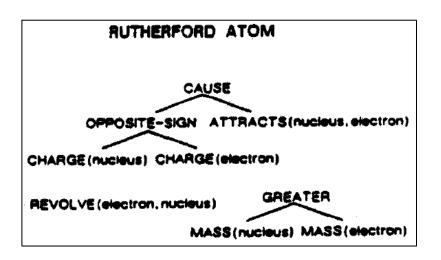


Example Models – Structure Mapping Engine

SME - Structure Mapping Engine (Falkenhainer et al., 19

- Component used in larger systems
- Similarity and extrapolation (candidate inferences)
- Finds deep structure to compare systems (analogs)
- Five SME features
 - Greedy merging, structural evaluation, incremental matching, ubiquitous predicates, and match filters
- Used in:
 - MAC/FAC (Forbus et al., 1995)
 - SEQL (Kuehne et al., 2000)
 - Companions cognitive architecture (Blass & Forbus, 2017; Forbus et al., 2009; Ribeiro & Forbus, 2021)







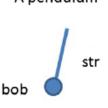


Structure Mapping Engine – Updated

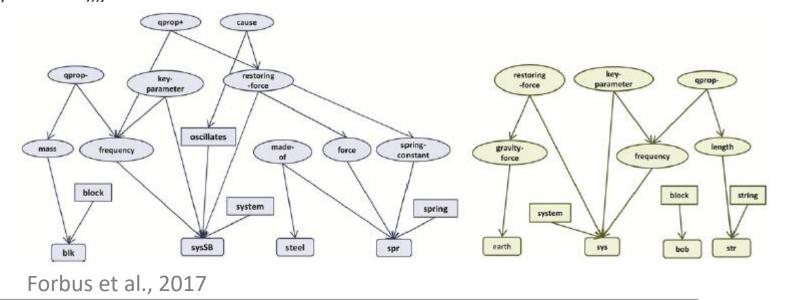
A spring-block oscillator



(spring spr) (block blk) (system sysSB) (made-of spr steel) (key-parameter sysSB (frequency sysSB)) (qprop+ (frequency sysSB) (spring-constant spr)) (qprop- (frequency sysSB) (mass blk)) (restoring-force sysSB (force spr)) (cause (restoring-force sysSB (force spr)) (oscillates sysSB))



(string str) (block bob) (system sys) (key-parameter sys (frequency sys)) (qprop- (frequency sys) (length str)) (restoring-force sys (gravity-force earth))))





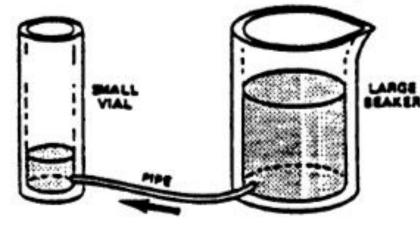


Structure Mapping Engine – Updated

Mapping 15 SME #1			SME #1	Expression Correspondences 5ME at [9 hema] Mapping 15		(Candidate Inferences SME [5 items] Mapping			
Score: 0.175	91			Base Item	Target Hern	Score	1			
				🐞 🗶 (force spr)	(gravity-force earth)	0.0082		Inference	Support	Extrapolation
A STATEMENT AND SERVICES	Base: spring-block-oscillator		🗮 🗮 (frequency sys)	(frequency sys)	0.0045					
Target: pendi	ulum			🛥 🗰 (spring-constant spr)	<pre>(gravitational-constant earth)</pre>	0.0042	0.50	(spring earth)	0.0005	0.9000
				(block hlk)	(block hob)	0.0005	2	(part-of sys earth)	0.0015	0.8500
Support	Base Item	Target Item	MH Score	😹 🗶 (kay-parameter sys (frequency sys))	(key-parameter sys (frequency sys))	0.0005	2		0.0068	0.5556
🗯 (5)	i∰ sys	🔆 sys	0.0560	(oprop+ (force spr) (spring-constant spr))	<pre>(qprope (gravity-force earth) (gravitational-constant earth))</pre>	0.0005		(qprop+ (frequency sys) (gravitational-constant earth))		
10-5-14	100 100	1000 DA125	0.0000	(restaring-force sys (force spr))	<pre>(prestaring-force sys (gravity-force earth))</pre>	0.0005	?	(qprop- (frequency sys) (mass bob))	0.0050	0.6296
2)	₩ blk	₩ bob	0.0080	(part-of sys blk)	(part-of sys bob)	0.0005		(cause (restoring-force sys (gravity-force earth))	0.0090	0.4857
* (2)	🕸 spr	🔆 earth	0.0992	* * (system sys)	<pre>(system sys)</pre>	0.0005		(oscillates sys))		0.1001



Structure Mapping Engine - Input



(defDescription simple-water-flow

entities (water beaker vial pipe)

expressions (((flow beaker vial water pipe) :name wflow)

AFRL

((pressure beaker) :name pressure-beaker)

((pressure vial) :name pressure-vial)

((greater pressure-beaker pressure-vial) :name >pressure)

((greater (diameter beaker) (diameter vial))

:name >diameter)

((cause >pressure wflow) :name cause-flow)

(flat-top water)

(liquid water)))

(defDescription simple-heat-flow

entities (coffee ice-cube bar heat)

expressions (((flow coffee ice-cube heat bar) :name hflow)

((temperature coffee) :name temp-coffee)

1 00 7 1

((temperature ice-cube) :name temp-ice-cube)

((greater temp-coffee temp-ice-cube) :name >temperature)

(flat-top coffee)

(liquid coffee)))

Falkenhainer et al., 1989

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Structure Mapping Engine – Output

Match Hypotheses:

(0.6500	0.0000)	(>PRESSURE >TEMP)
(0.7120	0.0000)	(PRESS-BEAKER TEMP-COFFEE
(0.7120	0.0000)	(PRESS-VIAL TEMP-ICE-CUBE
(0.9318	0.0000)	(BEAKER-6 COFFEE-1)
(0.6320	0.0000)	(PIPE-8 BAR-3)
0	0	0
٥	0	o

Global Mappings:

GRAD #1: (>PRESSURE >TEMPERATURE) (PRESSURE-BEAKER TEMP-COFFEE) (PRESSURE-VIAL TEMP-ICE-CUBE) (VFLOW HFLOW) Emaps: (beaker coffee) (vial ice-cube) (water heat) (pipe bar) Veight: 5.99 Candidate Inferences: (CAUSE >TEMPERATURE HFLOW) Gmap #2: (>DIAMETER >TEMPERATURE) (DIAMETER-1 TEMP-COFFEE) (DIANETER-2 TEMP-ICE-CUBE) (beaker coffee) (vial ice-cube) Laaps: Weight: 3.94 Candidate Inferences: Gaap #3: (LIQUID-3 LIQUID-5) (FLAT-TOP-4 FLAT-TOP-6) Laaps : (water coffee) Weight: 2.44 Candidate Inferences:

Falkenhainer et al., 1989

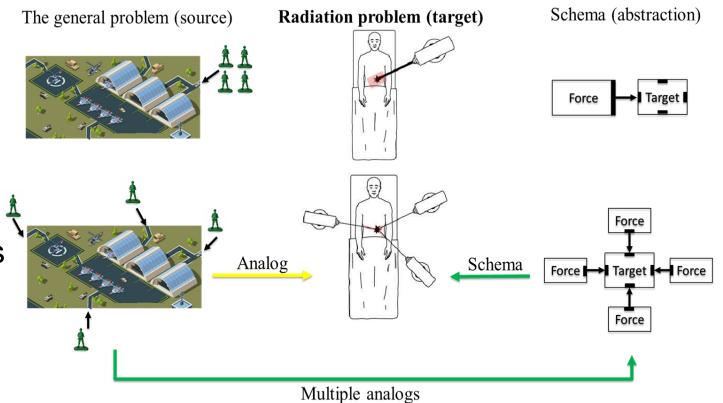


Analogical Reasoning – What is it?

Schemas and transfer in

problem solving (Gick & Holyoak, 1983)

- Analogy partial mapping and extension of attributes/relations
 - Not always noticed, include surface and deep structure
- Schema deep structure/relations
 - Effort and experience, can transfer







Analogical Reasoning Models - Comparison

Qualities	SME	ACT-R PM	
Input	Structured information - parsed text or processed visual information	Structured knowledge - abstract analogs with defined objects and relations, and chunk similaries	
New information and incremental input	Yes, can re-map/structure by starting over	Yes, but not as is. New structured knowledge must be given or added	
Mapping types	Surface, analogy, literal, and anomoly	Analogy. Could potentially do more with added structure/information and rules	
Mapping ability	Degree of similarity and structure	Exact match	
Inferences or extrapolation?	Yes	No	
Mapping/similarity/inference scores	Yes	No	
Interleaving of cog process	No, separate cognitive operations (map, retrieval)	Yes, mapping can be interleaved with cog processes	





Analogical Reasoning Models - Comparison

Qualities	SME	ACT-R PM	
Model tracing	Some	Yes, process, memory, attention, utility	
External guidance	Rules	Rules, goals, and "skills"	
Natural constraints	No, but match filters extract them from task?	Yes	
Scalabilty?	Yes	Not by itself, could with ML or additional model	
Gaps types?	Possible capability for: Homonym, cue, explanatory, memory (omission), metonymy	Possible capability for: Homonym, cue, explanatory, memory (omission), metonymy, rationality	
Knowledge base needed	Needs more, but less structured	Needs less, but needs processed information with more structure	
Computation speed	Relatively fast - parallel and serial	Likey very slow at symbolic level	
Complete model?	No, it is a component	No, it is an analog mapper	