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MARY A STATISTICS

High-throuhgput biology is yielding a vast amount of data the genome, transcriptional regulation and proteome of many microbial organisms.

- Yet, the complete metabolic network of even the simplest fully sequence living system has not been elucidated
- We want to develop computational inference methods to enhance the pace of metabolic pathway discovery



*Elucidating metabolic pathways through computational inference over biomolecular data

- Two intertwined predictive goals ...
 - Analysis: Piecing together plausible views of microbial metabolic pathways
 - Engineering: Rationally designing new metabolic capabilities
- Application to specific biological problems and experimental collaboration



*Traditional methods for experimental determination of pathways are labour-intensive and time-consuming

- There is no high- throughput experimental strategy yet for pathway discovery
- With the availability of whole microbial genomes it is possible to theoretically identify putative proteins and their functions, computationally
- Computational reconstruction of pathways is feasible



Understanding the complexity of biological systems requires an integrative approach

- Informatics is key for representing biochemical concepts and making them amenable to computation
- Computational approaches are crucial for inference over biological knowledge
- We are developing such a computational framework to support metabolic inference



Many proteins in microbial genomes have not be functionally characterized

- Piecing together functional characterizations of enzymes into plausible metabolic pathways is not straightforward
- Many microbial organisms have new enzymes and novel pathways -- how do we identify these ?



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Given and input compound **and an output compound, find a series of enzyme-catalyzed transformations that convert the input to the output**

- For example: What is the pathway from alpha-dglucose to pyruvate in E.coli ?
- In E.coli this series of enzyme catalyzed transformations is known as glycolysis



ALC: NO

Not really !

- For example, *H.pylori is responsible for peptic ulcers; treatments exist but there is no cure*
- There are many open questions about its its intermediary metabolic pathways
- How is glucose metabolised in H.pylori ?







Even reference or *standard* pathways are not always followed precisely in microbial organisms

- In many organisms alternative biochemical routes or *detours* have been observed (Cordwell, 1999)
- These alternative pathways can use known or unknown enzymes
- How do we infer such pathways in general computationally ?



Known pathway but some key enzymes are missing (from annotation)

- *i.* Homologues have diverged and undetectable by sequence similarity.
- ii.Enzyme(s) from another superfamily catalyze steps in
 pathway.
- *iii.There is a non-obvious pathway detour*



- M. When no known pathway exists between two compounds then the inference is harder. Consider,
 - i. A new sequence of known enzyme-catalyzed transformations are involved
 - ii. A biochemical pathway must be identified, de novo.That is, a plausible sequence of novel enzymatic functions must be identified



We represent biochemistry rationally to enable computations with it and to define novel types of biocatalytic functions

- This representation is the basis for:
 - Integrating available biomolecular and biochemical data
 - Making inferences about functions and pathways



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We have developed a computational representation of metabolism that resolves biocatalysis into two parts:

- The chemical component captures the chemical nature of the underlying transformations between compounds.
- The biological component captures the enzymatic roles of gene products in terms of specific transformations



We abstract metabolism as a hyperdim. state-space in which compounds are points and transformations are state-transitions

- Each compound is represented in *symbolic* terms by its chemical structure components. Eg: carbon dioxide
 - (CO2) = ((C 1)(O 2)(C=O 2))
- The representation also includes the molecular graph to infer adjacency of any atom or bond
- We have 10,429 compounds from KEGG



Transformations are state-transitions captured by Wector differences between states

- Transformation between alpha-D-glucose-6phosphate (adg6p) and alpha-D-glucose (adg) is represented as:
 - T(adg6p,adg) = x(adg6p)- x(adg)
 = ((P 1)(O 4)(P-O 3))
- We build transformations from 5,241 reactions





Each transformation is associated with enzymes Enzymes are described by EC numbers, gene names

- Enzymes can catalyze multiple transformations
- We have around 3,081 defined enzymes



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For each organism, we have the complete set of putative proteins and their assigned functions, including:

Enzymes

All Friday

- Transporters
- We also have all sequence data from SwissProt and GenBank
- We have the complete genomes for 100 organisms



By integrating a large amount of metabolic information we can now make inferences with it:

- Predict metabolic pathways from genomic data by finding plausible biochemical routes
- Predict biocatalytic functions from protein superfamilies to suggest possible functions of putative protein (from genomic data)



Since the sequencing of the first microbial genome, H.influenza, a number of computational methods have been developed to reconstruct reference pathways. Eg. Magpie, PathoLogic, and WIT

- Reconstruction is an important starting point for understanding pathways in an organism but there are generally many missing enzymes and gaps in such pathways
- We needed strategy to infer new pathways



Consider our of metabolism: compounds are states, transformations are state-transitions, and compounds have chemical successors

- We elucidate a metabolic pathway computationally by state-space search
- Each predicted pathway is series of state-transitions
- This produces a combinatorially large number of possible solutions. How can we pick a reasonable subset ?



Heurisic search is an informed search technique that uses a best-first algorithm to explore a statespace to find a pathway from initial to final state.

- As opposed to blind search (BFS or DFS), informed search methods use an evaluation function (F) to measure the cost of a path
- F can be calculated in different ways:
 - Greedy minimize cost to goal (F=H)
 - A* minimize sum of cost so far (G) and cost to goal
 (F=G+H)



To predict metabolic pathways by heuristic search, we must calculate the heuristic evaluation function, F

- In general, there are complex factors that determine the cost of a pathway. We wanted a simple concept to compute F
- We decided to test the chemical distance between states to estimate biochemical cost of a pathway from x(0) to x(L), where x(m) is an intermediate state in the pathway:
 - F(0,m,L) = G(0,m) + H(m,L)



Based on this algorithm, have developed PathMiner, an interactive computational framework for automated metabolic pathway elucidation

 A* search used in PathMiner always finds a pathway that is optimal in *F, not the shortest pathway, and A* search is significantly faster than blind search*

We are using PathMiner for elucidating

- Microbial pathways from genomic annotations
- Synthetic pathways for engineering



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	FROM alpha-d-glucose	<u></u>
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We are testing PathMiner by investigating pathways in different microbes: *H.pylori*, *D.radiodurans and S.oneidenosis MR-1*

- In H.pylori we found a number of pathways that are congruent with experimentally determined pathways, including:
 - Glucose metabolism
 - Pentose phosphate pathway
 - TCA





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0 PHOSPHOENOLPYRUVATE	((C 3) (0 6) (P 1) (C-C 1) (C-O 2) (C=C 1) (C=O 1) (0-P 3) (0=P 1))
(EC_4.1.1.49)	(PHOSPHOENOLPYRUVATE_CARBOXYKINASEATP)
1 OXALOACETATE	((C 4) (0 5) (C-C 3) (C-0 2) (C=0 3))
(EC_1.1.1.37)	(MALATE_DEHYDROGENASE)
2 S-MALATE	((C 4) (0 5) (C-C 3) (C=0 2))
(EC_4.2.1.2)	(FUMARATE_HYDRATASE)
3 FUMARATE	((C 4) (0 4) (C-C 2) (C-C 1) (C=C 1) (C=C 2))
(EC_3.7.1.2)	(FUMARYLACETOACETASE)
4 4-FUMARYLACETOACETATE	((C 8) (0 6) (C-C 6) (C-O 2) (C=C 1) (C=O 4))
(EC_5.2.1.2)	(MALEYLACETOACETATE_ISOMERASE)
5 4-MALEYLACETOACETATE	((C 8) (0 6) (C-C 6) (C-O 2) (C=C 1) (C=O 4))
(EC_1.13.11.5)	(HOMOGENTISATE_1-2-DIOXYGENASE)
6 HOMOGENTISATE	((C 8) (0 4) (C-C 5) (C-O 3) (C=C 3) (C=O 1))
(EC_1.13.11.27)	(4-HYDROXYPHENYLPYRUVATE_DIOXYGENASE)
7 3-4-HYDR0XYPHENYLPYRUVATE	((C 9) (0 4) (C-C 6) (C-O 2) (C=C 3) (C=O 2))
(EC_1.3.1.43 EC_1.3.1.52 EC_1.3.1.12)	(CYCLOHEXADIENYL_DEHYDROGENASE 2-METHYL-BRANCHED-CHAIN-ENOYL-COA_REDUCTASE PREPHENATE_DEHYDROGENASE)
8 PREPHENATE	((C 10) (H 1) (0 6) (C-C 8) (C-H 1) (C-O 3) (C=C 2) (C=O 3))
(EC_5.4.99.5)	(CHORISMATE_MUTASE)
9 CHORISMATE	((C 10) (0 6) (C-C 6) (C-0 5) (C=C 3) (C=0 2))

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Features	19	17	17	15	27	27	24	26	34	32
Successors	10	10	4	9	3	2	2	3	4	5
G (0, m)	0	12.0	14.0	18.0	492.56506	492.56506	501.56506	505.56506	515.56506	523.5650
H (m, L)	23	17	15	17	9	9	8	6	8	0
F (0, m, L)	23	29.0	29.0	35.0	501.56506	501.56506	509.56506	511.56506	523.56506	523.5650

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Pathway 2 From PHOSPHOENOLPYRUVATE to CHORISMATE

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0	ALPHA-D-GLUCOSE	((C 6) (0 6) (C-C 5) (C-0 7))
	(EC_5.1.3.3)	(ALDOSE_1-EPIMERASE)
1	BETA-D-GLUCOSE	((C 6) (0 6) (C-C 5) (C-O 7))
	(EC_1.1.1.47)	(GLUCOSE_1-DEHYDROGENASE)
2	D-GLUCONO-1-5-LACTONE	((C 6) (0 6) (C-C 5) (C-0 6) (C=0 1))
	(EC_3.1.1.17)	(GLUCONOLACTONASE)
3	D-GLUCONIC_ACID	((C 6) (0 7) (C-C 5) (C-0 6) (C=0 1))
	(EC_2.7.1.12)	(GLUCONOKINASE)
4	6-PH0SPH0-D-GLUCONATE	((C 6) (0 10) (P 1) (C-C 5) (C-0 6) (C=0 1) (0-P 3) (0=P 1))

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Π	0	1	2	3	4	5	6
Features	24	24	24	25	33	27	28
Successors	12	7	3	4	4	5	8
G(O,m)	0	0.0	2.0	3.0	11.0	17.0	20.0
H(m,L)	10	10	10	9	5	3	0
F(O,m,L)	10	10.0	12.0	12.0	16.0	20.0	20.0



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Pathway 4 From ALPHA-D-GLUCOSE to D-RIBOSE_5-PHOSPHATE

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It is important to consider pathways in the context of broader biochemical processes.

- One way to elucidate the pathways in an organism is to analyze the complete network using functional annotations of genes and known transporters
- We have built a complete network visualization of D.radiodurans, which we are using to analyze gaps and putative proteins that can fill those gaps.





Given the large amount of sequence data how accurately can we infer biocatalytic roles ?

- By systematically computing the correlation of known enzymatic functions with sequence similarity we find:
 - Only 35% of enzymatic functions can be assigned with confidence
 - There are many cases of false positives and false negatives



AN AN AM

We begin with a widely used classification scheme, the Enzyme Commission (EC) nomenclature

- The EC defines six broad biocatalytic categories
- Each category has four levels of specification
- There are about 3,500 specific reaction types across all known enzymes
- Though not exhaustive, it covers most enzymes



An EC function is a string of four digits, each number signifying the level in the hierarchy. E.g. EC 1.2.3.4 is oxalate oxidase:

- Class 1: Oxidoreductase
- Sub-class 2: Acts on aldehyde or oxo group of donor
- Sub-sub-class 3: The acceptor is oxygen
- Serial number 4: The specific reaction: oxalate+O2<=> hydrogen peroxide+CO2









The EC classification is manually derived the differences between levels are not consistent across the functional categories

- The scheme does not capture function uniquely. (Eg. Enzymes that transfer groups share characteristics with ligases)
- The hierarchical organization does not allow complex functions to share multiple characteristics. (Eg. A transferase is like a ligase)
- These factors make EC identifiers difficult to compute with











Protein function is a property of three dimensional structure and it is hard to make inferences from linear sequence

- Biocatalytic function definitions based on the EC are not always precise and computable
- Specific issues:

- Distant homologues are hard to identify
- Proteins in superfamilies have divergent functions
- We need sensitive and specific methods



Machine Learning (ML) can be used to induce rules that can characterize proteins according to functional classes

Strategy:

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- Identify superfamilies as relevant data sets for training as they contain examples of divergent functions
- Functionally relevant representations of proteins based on conserved modules
- Induction algorithms to infer hypothesis about the correlation between the proteins and their biocatalytic functions





DRTS_PLACH		Т			1.5.	1.3.1
DRT1_ARATH	Т				1.5.	1.3.1
DRT2_ARATH	Т				1.5.	1.3.1
DRTS_LEIAM					1.5.	1.3.1
DRTS_LEIMA					1.5.	1.3.1
DRTS_PLAFK	Т				1.5.	1.3.1
DRTS_DAUCA					1.5.	1.3.1
DRTS_TOXGO					1.5.	1.3.1
TYSY_MOUSE					2.1.	1.45.
TYSY_RAT					2.1.	1.45.
TYSY_HUMAN			Ē		2.1.	1.45.
TYSY_PNBCA					2.1.	1.45.
TYSY_HSVSA					2.1.	1.45.
TYSY_HSVAT					Z.1.	1.45.
TYSY_CANAL					2.1.	1.45.
TYSY_YEAST					2.1.	1.45.
TYSY_CRYNE					2.1.	1.45.
DYR_HSVS7					1.5.	1.3.1
DYR_HSVSC					1.5.	1.3.1
TYSY_VZVD					2.1.	1.45.
DYR_MESAU					1.5.	1.3.1
DYR_MOUSE					1.5.	1.3.1
DYR_PIG					1.5.	1.3.1
DYR_HUMAN					1.5,	1.3.1
DYR_BOVIN					1.5.	1.3.1
DYRA_CITFR					1.5.	1.3.1
DYRA_ECOLI					1.5.	1.3.1
DYRA_ENTAE					1.5.	1.3.1
DYR_HSVSA					1.5.	1.3.1
DYRA_KLEAE					1.5.	1.3.1
DYR_CHICK					1.5.	1.3.1
TYSB_BACSU					2.1.	1,45.
TYSY_ECOLI					2.1.	1.45.
DYRA_STAAU					1.5.	1.3.1
DYRB_STAAU					1.5.	1.3.1
TYSY_SHIFL					2.1.	1,45.
TYSY_LACCA					2.1.	1.45.
TYSY_MYCGE					2.1.	1.45.
TYSY_STAAU					2.1.	1.45.
DYRB_ECOLI				+	1.5.	1.3.1
DYRC_ECOLI				+	1.5.	1.3.1
TYSY_BPT4					2.1.	1.45.
DYR7_ECOLI				+	1.5.	1.3.1
DYR_AEDAL					1.5.	1.3.1
DYR_DROME					1.5.	1.3.1
DYRA_HAEIN					1.5.	1.3.1
DYR3_SALTY					1.5.	1.3.1

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CIERC_SCALAN							1.6.4.2
GSRC_PEA							1.6.4.2
GSHC_ARATE							1.6.4.2
GSHR_HUMAN							1.6.4.2
GSHR ORYSA	П					+	1.6.4.2
OSHIL ARATH							1.6.4.2
GSIIR_BCOLT							1.6.4.2
GISTIR_HATUN							1.6.4.2
GSHE_PSEAE							1.6.4.2
OSHR_VEAST							1.6.4.2
GSHR_BURCE							1.6.7.2
USHN ANASP							1.6.4.2
TYIR_TRYOD	H						1.6.4.8
TYTE_JEYBD	H						1,6,4,8
TYTE LEDG	H						1.6.4.8
TYTE_TRYCE.	H						1.6.4.8
TYTE_CRIPA	H						1.6.4.8
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NIRB KLEPN DIDIA_BACSU R34K_CLOPA							1.6.95.3 1.6.95.3 NE
NIRB KLEPN DIDYA_BACSU R34K_CLOPA NIRB_DCOLI							1.6.95.3 1.6.95.3 NE 1.6.6.4
NIRB KLEPN DIDYA_BACSU R94K_CLOPA NIRB_BCOLI HIRE_PSPCT. DIDYA_BACSD							1.6.95.3 NE 1.6.6.4 1.18.1.1
NIRB KLEPN DIDYA_BACSU R94K_CLOPA NIRB_BCOL RURE_PSECT. DHOYA_BACSP DAIM CLIMM							1.6.95.3 NE 1.6.6.4 1.18.1.1 1.6.95.3
NRB KLEPA DIDYA_BACSU RBK_CLOPA NRB_BCOLI RURE_PSECT DIDYA_RACSP BATH_EUBSP AMER_BATSY							1.6.95.3 NE 1.6.5.4 1.18.1.1 1.6.95.3 NE
NIRB KLEPA DIBYA_BACSU K34K_CLOPA NIRB_BCOLI HURF_PSPCT. DHIYA_RACSP BAIH_EUBSP AHFT SAUTY							1.6.95.3 NE 1.6.5.4 1.18.1.1 1.6.95.3 NE NE
NIRB KLEPA DIBYA_BACSU K34K_CLOPA NIRB_BCOLI HURF_PSPCT. DHDYA_RACSP BAIH_EUBSP AHFT SALTY NASD EACSU NASO EACSU							1.6.5.4 1.6.95.3 NE 1.6.6.4 1.18.1.1 1.6.95.3 NE NE NE 1.6.5.4
NIRB KLEEN DIEVA_BACSU REAR_CLOPA NIRB_BCOLI BURE_PREEN DIEVA_RACSP BAIH_EURSP AHFT SAUTY NASD_FACSU NADO_THERR							1.6.5.4 1.6.95.3 NE 1.6.6.4 1.18.1.1 1.6.95.3 NE NE 1.6.5.4 NE
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NIRB KLEEN DIDYA_BACSU NIRB_CODE NIRB_DODU BAIRE_BYPY, DIDYA_RACSP BAIR_EUBSP AARP SALTY NASD EACSU NASD EACSU SACOX_BACSP RENG_BIRCS							1.6.6.4 1.6.95.3 NE 1.6.6.4 1.8.1.1 1.6.93.3 NE NE 1.6.5.4 NE 1.6.5.4 NE 1.5.3.1 1.18.1.3
NIRU KLEEN DIDYA DACSU RUHK CLOPA NIRU DOOL MIRT DOOL DIDYA DACSU BAIR EUBSP AHET SALTY NASO EACSU NADO THEOR SACCEACSIN DIPYA DIDKCE TODA FREEU							1.6.6.4 1.6.95.3 ME 1.6.6.4 1.6.95.3 ME ME 1.6.95.4 ME 1.6.95.4 ME 1.5.3.1 1.18.1.3 1.18.1.3 1.18.1.3
NIRU KLEEN DIDYA_DACSU NIRU CLOPA NIRU CLOPA NIRU CLOPA NIRU CLOPA NIRU CLOPA DINYA_NACSP BAIH_EUBSP AHPT SALTY NASD FACSU NIADO_THEOR SACS_FACSU BRHC, DIIRCE TCDA_PSEPU TRYS_FERCH.							1.6.6.4 1.6.95.3 RE 1.6.6.4 1.8.08.3 RE 1.6.5.4 NE 1.6.5.4 NE 1.6.5.4 NE 1.5.3.1 1.18.1.3 1.18.1.3 1.18.1.5 1.18.1.5
NIRB KLEEN DIDYA, BACSU NIRB, CLOPA NIRB, BOOLI RUHE, JESPET, DIDYA, RACSP BAHL, EURSP BAHL, EURSP BAHL, EURSP NASD, BACSU NIADO, THEOR SACK, BACSU NIADO, THEOR REHE, DIREC TRNSB, PERCH, TRNSB, PERCH, TRNSB, PERCH,							1.6.6.4 1.6.95.3 NE 1.6.6.4 1.8.08.3 NE 1.6.5.4 NE
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NIRS KLEEN DIDYA_BACSU NIRS KLEEN AHR, CLOPA NIRS JOOUL BAIRE_BYST, DHYA_RACSP BAIRI, EUBSP AHRT SALTY NADO_THEMR SACIX_BACSP RENG, NIRCE TODA_REPU NING FACSP ENCONTRAS FACSP ENCONTRAS FACSP ENCONTRAS FACSP ENCONTRAS FACSP ENCONTRAS FACSP ENCONTRAS FACSP ENCONTRAS FACSP							1.6.6.4 1.6.95.3 NE 1.6.6.4 1.78.1.1 1.6.98.3 NE NE 1.6.9.4 NE 1.5.3.1 1.18.1.3 1.18.1.3 1.6.4.5 1.18.1.3 1.6.4.5 1.18.1.3 1.6.6.4
NIRU KLEEN DIDYA_DACSU NIRU KLEEN NIRU LODA NIRU LODA NIRU LODA DIDYA_RACSU BAIR EUBSP ART SALTY NASO FACSU BAIR EUBSP NADO THEOR SACCEACSU DIDYA SAEN TRYB RAEN BAIR OFFEN RAY SHOUND							1.6.6.4 1.6.95.3 RE 1.6.6.4 1.18.1.1 1.6.98.3 RE 1.6.5.4 NE 1.6.5.4 NE 1.5.3.1 1.18.1.3 1.18.1.3 1.6.4.5 1.6.6.4 NE 1.6.6.4
NIRB KLEEN DIDYA, BACSU RUHK, CLOPA NIRB, BOOLI RUHK, RACSP BAHH, EURSP BAHH, EURSP BAHH, EURSP BAHH, EURSP NASD BACSU NIADO, THEOR SACK, BACSU NIADO, THEOR REHC, BHIRCH TRNB, BAERU TRNB, FAREU TRNB, FAREU TRNB, FAREU TRNB, FAREU TRNB, FAREU TRNB, FAREU TRNB, FAREU TRNB, FAREU TRNB, FAREU							1.6.6.4 1.6.95.3 NE NE 1.6.08.3 NE 1.6.08.4 NE 1.6.08.4 NE 1.6.08.4 NE 1.5.3.1 1.18.1.3 1.6.0.5
NRB KLEP DIDYA, BACSU NRB, CLOPA NRB, DOOLI RHRF, JSPCY, DIDYA, RACSP BAHH, EUBSP AAFFT SALTY NADO, THEBR SACK, BACSP NADO, THEBR SACK, BACSP TODA, FREP TODA, FREP TRXB, JERNET RAC, THRSP TRXB, JENET TRXB, JENET RAC, THRSP TRXB, JMYCL F, YHYL, ECOLI						THE PERSON PERSON AND A DESCRIPTION OF A	1.6.6.4 1.6.95.3 NE 1.6.6.4 1.6.95.3 NE 1.6.5.4 NE 1.6.5.4 NE 1.5.3.1 1.18.1.3 1.6.4.5 1.6.4.5 1.6.4.5 NE
NIRS KLEP DIDYA_BACSU NIRS_CODE NIRS_BOOL NIRS_DOOL NIRS_DOOL NIRS_CODE DAYA_RACSP BAIR_EUBSP AAFF SALTY NASD FACSP RENC, NIRCP TODA_PSEPU NIRCPACSP NIRCPACSP NIRCPACSP NIRCPACSP NIRCPACSP NIRCPACSP YERCENTSP DAY_PITER YERCECOL DHYA BCCLI						THE PERSON STREET STREET	1.6.6.4 1.6.95.3 NE 1.6.6.4 1.6.98.3 NE NE 1.6.98.4 NE 1.5.3.1 1.18.1.3 1.18.1.3 1.18.1.3 1.6.4.5 1.18.1.5 1.6.4.5 1.6.4.5 NE
NIRS KLEEN DIDYA_BACSU NIRS KLEEN RAHK_GLOPA NIRS_BECT DHOYA_BACSD BAIR_EUBSP AHET SALTY NASD FHEDB SACIX_BACSD BAIR_EUBSP NADO_THEDB SACIX_BACSD BAIR_BAEN BAIDY, THEDB SACIX_BACSD BAIR_BAEN BAIDY, SHEPU NIR_EMENT BAIX_BIRSD DHYA BCCLI DHYA BCCLI OHDM YEAST						THEFT PERSON AND A DESCRIPTION OF	1.6.6.4 1.6.95.3 RE 1.6.6.4 1.18.1.1 1.6.98.3 RE 1.6.5.3.1 1.18.1.3 1.18.1.3 1.18.1.3 1.6.4.5 1.6.4.5 NE 1.6.4.5 NE 1.6.4.5 NE

. 11. منظم معتبر معتبر المنار المائم ومعرد شامر المائم المائم المائم المتار المعام المعرد والمار الم

We have built classifiers for the inference of the biocatalytic potential of a putative protein

- Efficiently annotate each ORF in a genome with putative enzymatic functions
- Vary the sensitivity and specificity of function inference
- Search for plausible protein candidates with a biocatalytic function



We can infer metabolic pathways from genomic data, or just synthetic pathways, through heuristic search

- We can accurately assign enzymatic functions to putative proteins by machine learning.
- By combining function inference with pathway search, we can improve predictions further



People

A MARINE STATISTICS

- Daniel McShan (Ph.d. Student)
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