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Autocatalytic chemical networks preceded proteins and RNA in evolution

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27 **Abstract**

28 Modern cells embody metabolic networks containing thousands of elements and form
29 autocatalytic molecule sets that produce copies of themselves. How the first self-sustaining
30 metabolic networks arose at life's origin is a major open question. Autocatalytic molecule sets
31 smaller than metabolic networks were proposed as transitory intermediates at the origin of
32 life, but evidence for their role in prebiotic evolution is lacking. Here we identify reflexively
33 autocatalytic food-generated networks (RAFTs)—self-sustaining networks that collectively
34 catalyze all their reactions—embedded within microbial metabolism. RAFTs in the metabolism
35 of ancient anaerobic autotrophs that live from H₂ and CO₂ generate amino acids and bases, the
36 monomeric components of protein and RNA, and acetyl-CoA, but amino acids and bases do
37 not generate metabolic RAFTs, indicating that small-molecule catalysis preceded polymers in
38 biochemical evolution. RAFTs uncover intermediate stages in the origin of metabolic networks,
39 narrowing the gaps between early-Earth chemistry and life.

40

41 **Keywords:** autocatalysis, autocatalytic networks, metabolism, origin of life, archaea,
42 bacteria, methanogens, acetogens, LUCA

43

44 **Introduction**

45 Cells are autocatalytic in that they require themselves for emergence. The origin of the first
46 cells from the elements on the early Earth roughly 4 billion years ago (Baross, 2018; Betts et
47 al., 2018; Varma et al., 2018; Tashiro et al., 2017) must have been stepwise. The nature of
48 autocatalytic systems as intermediate states in that process is of interest. Autocatalytic
49 molecule sets are simpler than cellular metabolism and produce copies of themselves if
50 growth substrates for food and a source of chemical energy for thermodynamic thrust are
51 provided (Fuchs, 2011; Goldford et al., 2017; Semenov et al., 2016). In theory, sets of organic

52 molecules should be able to form autocatalytic systems (Dyson, 1982; Eigen and Schuster,
53 1977; Kauffman, 1971), which, if provided with a supply of starting 'food' molecules, can
54 emerge spontaneously and proliferate via constraints imposed by substrates, catalysts, or
55 thermodynamics (Kauffman, 1986). Autocatalytic sets have attracted considerable interest as
56 transitory intermediates between chemical systems and genetically encoded proteins at the
57 origin of life (Hordijk et al., 2010; Kauffman, 1986; Smith and Morowitz, 2004; Sousa et al.,
58 2015), but they have not been identified in non-enzymatic metabolic networks so far and
59 evidence for their existence during prebiotic evolution is lacking.

60

61 Of special interest for metabolic evolution are a class of mathematical objects called
62 Reflexively Autocatalytic Food-generated networks—RAFTs—in which each reaction is
63 catalyzed by a molecule from within the network and all molecules can be produced from a
64 set of food molecules by the network itself (Hordijk and Steel, 2004). Small chemical systems
65 resembling RAFTs have been constructed in the laboratory (Ashkenasy et al., 2004; Semenov
66 et al., 2016; Vaidya et al., 2012), although still far from the scale of cellular metabolism,
67 which is composed of thousands of reactions. Modern cellular metabolism is enzyme-based,
68 but >60% of enzyme mechanisms described to date involve one or more cofactors (Ribeiro et
69 al., 2018) and 40% of all proteins crystallized have a bound metal relevant to their function
70 (Guengerich, 2016). RAFTs can thus be identified in modern metabolism (Sousa et al., 2015)
71 by attributing the catalysis of enzymes to their metals and cofactors in prebiotic evolution
72 (Argueta et al., 2015; Martin and Russel, 2007; Stockbridge et al., 2010; Varma et al., 2018;
73 White, 1976; Zabinski and Toney, 2001). If autocatalytic chemical networks antedate
74 genetically encoded proteins, cofactor-dependent RAFTs might have been involved and, if so,
75 should have left evidence for their existence in modern metabolic networks.

76

77 In search of RAFs, we investigated different levels of ancient metabolism preserved in
78 modern cells. Starting with the biosphere level of the KEGG database, we first removed all
79 eukaryote-specific reactions, and then peeled back one more layer of time by examining
80 anaerobic metabolism. The detection of a large RAF in anaerobic prokaryotic metabolism
81 prompted us to ask whether RAFs are also preserved in the metabolism of ancient anaerobic
82 autotrophs that trace to the last universal common ancestor, LUCA (Weiss et al., 2016). As
83 far back as we could look in metabolic evolution, RAFs were found. They were found in the
84 metabolism of the acetogenic bacterium *Moorella thermoacetica* and the methanogenic
85 archaeon *Methanococcus maripaludis*, primitive lineages that live on the simplest source of
86 carbon and energy known, the H₂-CO₂ redox couple (Baross, 2018; Fuchs, 2011; Martin and
87 Russel, 2007; McCollom and Seewald, 2007; Müller et al., 2018; Weiss et al., 2016). Their
88 RAFs furthermore intersect in a primordial network that generates amino acids, nucleosides,
89 and acetyl-CoA from a starting set of simple food molecules, shedding light on the nature of
90 autocatalytic networks that existed before the first cells arose from the elements on the early
91 Earth.

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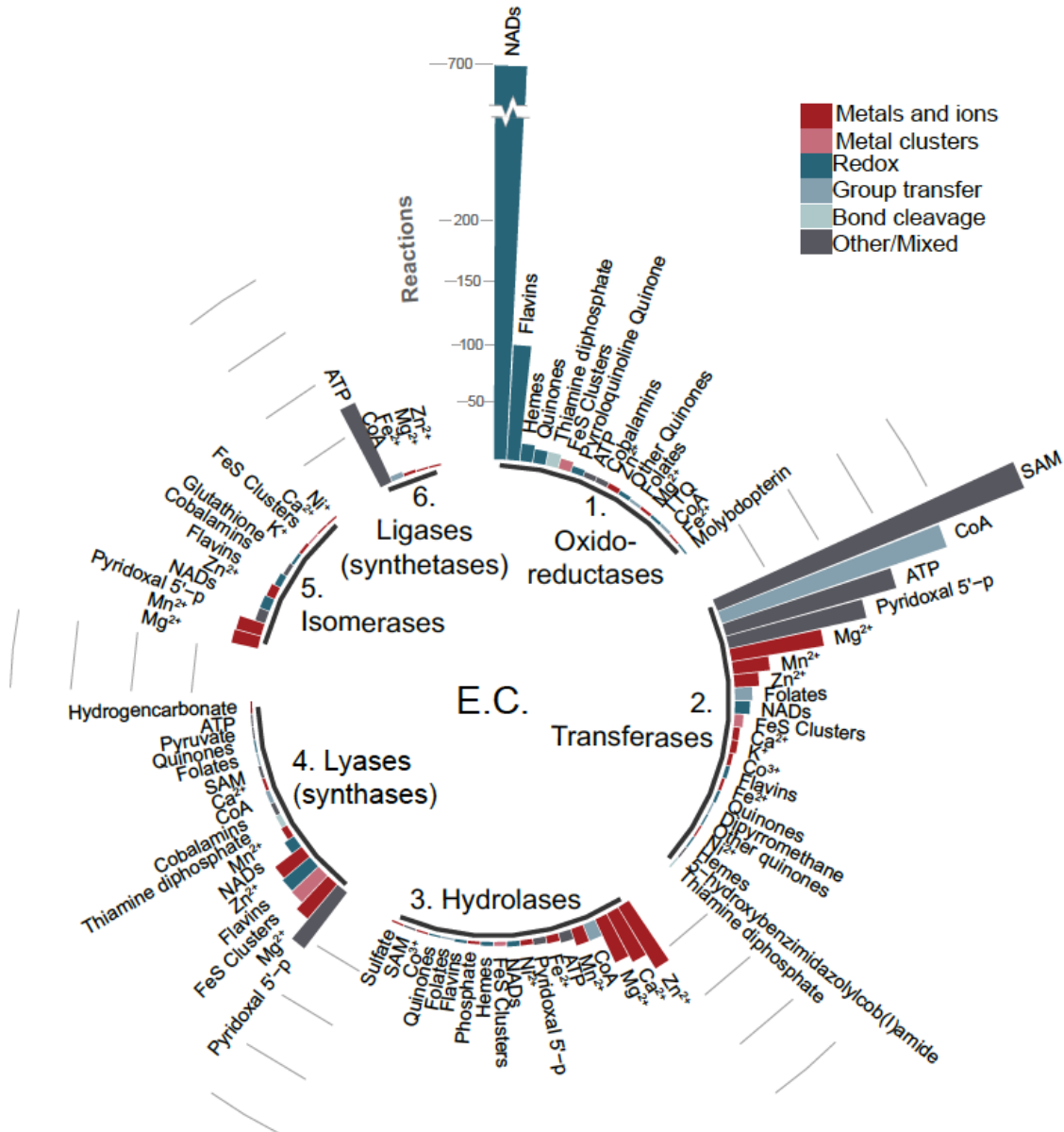
94 **Results**

95 **Two-thirds of global prokaryotic metabolism can be annotated with small-molecule** 96 **catalysis**

97 In search of RAFs in 4-billion-year-old metabolism, we started from all 10,828 KEGG
98 reactions and purged the set of non-primordial reactions in two pruning steps. First, we
99 removed reactions assigned only to eukaryotes. Such reactions are not primordial because
100 eukaryotes arose less than 2 billion years ago (Betts et al., 2018). Second, we excluded O₂-
101 dependent reactions, because O₂ is a product of cyanobacterial photosynthesis, which arose

102 about 2.4 billion years ago (Fischer et al 2016). These pruning steps left 5847 enzyme-
103 associated reactions, 66% of which involve at least one cofactor. The addition of 147
104 spontaneous reactions generated a global network comprising 5994 reactions and 5723
105 metabolites (see Materials and Methods, **Figure S1 and Table S1A**). The cofactors involved
106 in this ancient anaerobic network are distributed among the five different Enzyme
107 Commission (E.C.) classes as shown in **Figure 1**. Metal catalysis is widespread across all
108 classes of metabolism, and NADH dominates the oxido-reductase reactions. The network
109 comprises 70% of the initial enzymatic reaction network before removal of O₂-dependent and
110 eukaryote-specific reactions, indicating that most metabolism was invented in the anaerobic
111 world (Raymond and Segrè, 2006).

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Figure 1. Catalysts in global oxygen-independent prokaryotic metabolism.

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The catalysis-annotated network separated by Enzyme Commission (EC) classes with the

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corresponding cofactors for each. Cofactors are grouped (legend, top-right) according to their

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function in catalysis.

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Autocatalysis in global metabolism expands with a small set of cofactors

122 The largest possible RAFs (maxRAFs) in a network are of interest because they represent its
123 largest component of autocatalytic complexity. **Figure 2A** shows a schematic representation
124 of a RAF within a metabolic network. The maxRAFs in the global prokaryotic O₂-
125 independent network were identified for different food sets, that is, molecules provided by the
126 environment (**Table S2**). An inorganic food set containing H₂O, H₂, H⁺, CO₂, CO, PO₄³⁻,
127 SO₄²⁻, HCO₃⁻, P₂O₇⁴⁻, S, H₂S, NH₃, N₂, all metals, FeS clusters and other metal clusters, a
128 generalist acceptor, donor, and metal produced a minute maxRAF with eight reactions linking
129 ammonia, carbon, and sulfide transformations. The addition of formate, methanol, acetate,
130 and pyruvate, which are central metabolites with experimental evidence for synthesis from
131 CO₂ and metals (Varma et al., 2018), doubles the maxRAF size to 16 reactions. In principle,
132 the addition of organic cofactors (**Table S2**) to the food set should generate larger maxRAFs.
133 Sequential addition of the eight most frequent cofactors identified in the last universal
134 common ancestor's (LUCA's) proteins (Weiss et al., 2016) to the metal-CO₂ food set
135 expanded the maxRAF from 16 to 914 reactions (**Figure 2B**). Addition of all cofactors
136 germane to the anaerobic network generates a maxRAF with 1335 reactions spanning 25% of
137 the starting anaerobic network. Sequential addition of the eight compounds that were most
138 frequent in that maxRAF, to the metal-CO₂ food set, expands the maxRAF from 16 to 1066
139 reactions, whereas sequential addition of the five compounds with the greatest impact (upon
140 removal from the food set) on anaerobic maxRAF size followed by the three most frequent in
141 the largest maxRAF yields a final maxRAF of 1248 reactions (**Figure 2B**). These results
142 indicate that RAFs can grow in size through sequential incorporation of organic cofactors
143 (**Figure 2B**). RAFs can thus provide structure, contingency, increasing complexity, and
144 direction to interactions among molecule food sets, given a sustained geochemical source of
145 carbon, energy, and electrons.

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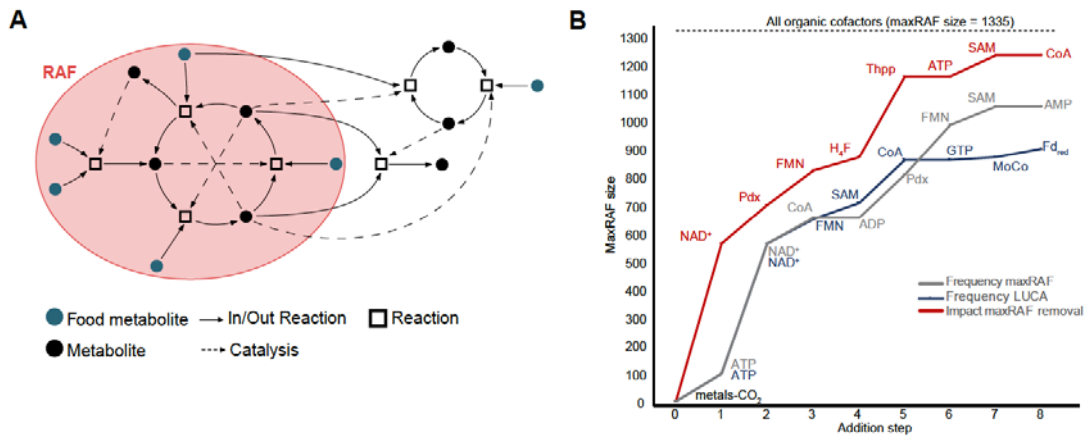


Figure 2. Autocatalysis in global metabolism expands with a small set of cofactors.

(A) Schematic depiction of a reflexively autocatalytic food-generated network (RAF)

highlighted (red ellipse) in a metabolic network. Food metabolites (green circles) may enter the RAF allowing subsequent reactions (squares) to occur and other metabolites (black

circles) to be produced. Each reaction is catalyzed by a metabolite in the network (catalysis

shown in dashed arrows). (B) Increasing maxRAF sizes with the sequential addition to the

food set of the organic cofactors (i) with the highest impact on maxRAF size upon removal

(red) (ii) most frequent in the maxRAF with all organic cofactors added (grey), and (iii) most

frequent in enzymes predicted to be in LUCA (Weiss et al., 2016) (blue) (Pdx – pyridoxal 5-

phosphate; H₄F – tetrahydrofolate, Thi – thiamine diphosphate, MoCo – molybdopterin; Fd_{red}

– reduced ferredoxin). Top dashed line shows the maxRAF size obtained when all organic

cofactors are added to the food set.

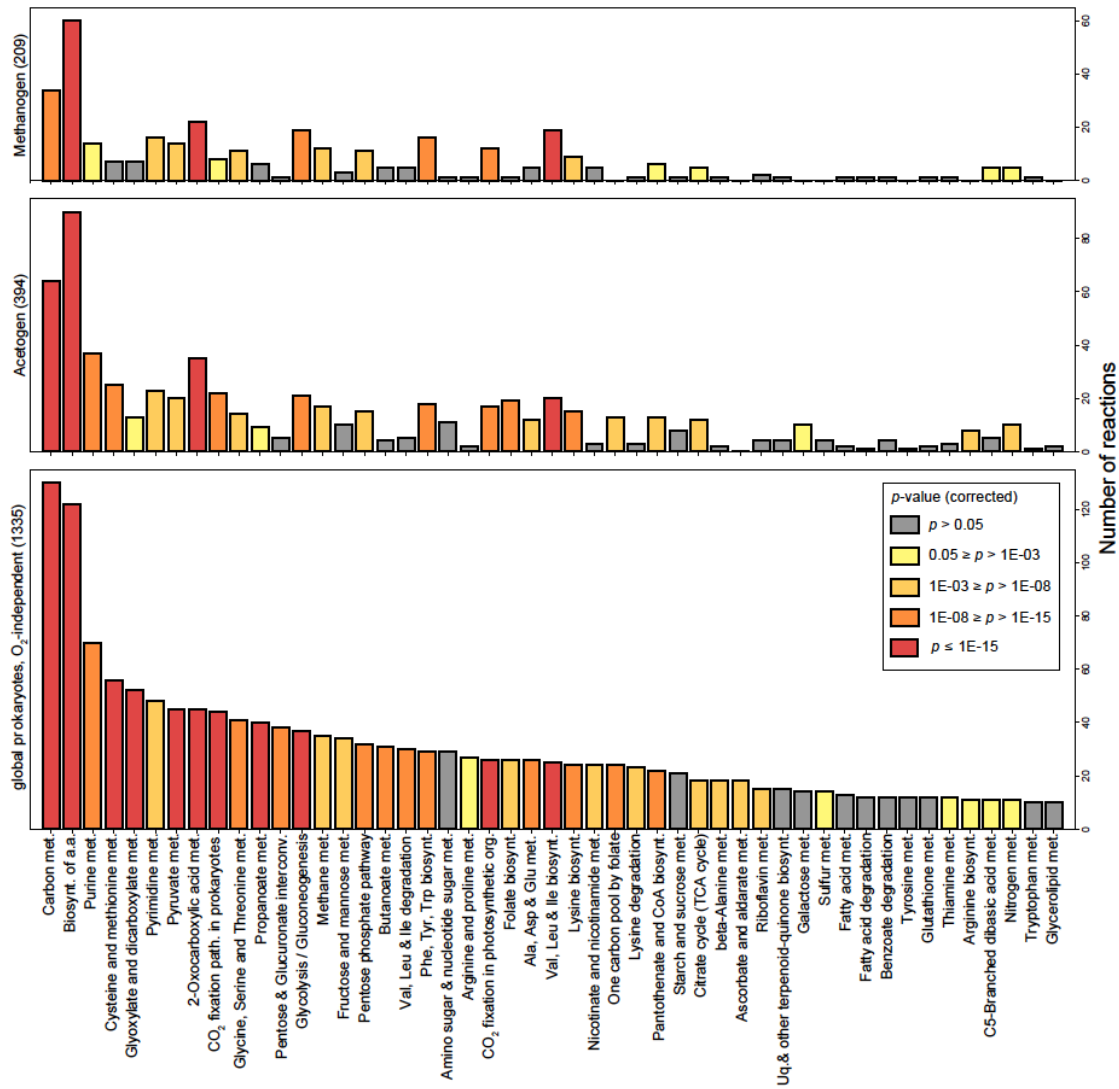
Autocatalytic networks point to an early autotrophic metabolism

If autocatalytic sets were instrumental at the origin of metabolism (Kauffman, 1986), lineages with a physiology very similar to that of the first cells should harbor the most ancient RAFs.

Several lines of evidence indicate that methanogens and acetogens reflect the ancestral state

of microbial physiology: they live on the simplest source of carbon and energy known, the

167 H₂-CO₂ redox couple (Baross, 2018; Fuchs, 2011; Martin and Russell, 2007; McCollom and
168 Seewald, 2007; Müller et al., 2018; Weiss et al., 2016), they assimilate geochemically-
169 generated carbon species (Stupperich and Fuchs 1984; Lang et al. 2010), they generate ATP
170 from CO₂ fixation (Fuchs, 2011), their core bioenergetic reactions occur abiotically in
171 hydrothermal vents (McCollom and Seewald, 2007; McDermott et al., 2015) and under
172 laboratory conditions (Varma et al., 2018), their ecology and gene trees link them to LUCA
173 (Weiss et al., 2016), and they still inhabit primordial habitats within the crust today (Ijiri et al.
174 2018). Subsets of the global prokaryotic O₂-independent network were obtained by parsing
175 the genomes of the acetogen *Moorella thermoacetica* (Ace) and the methanogen
176 *Methanococcus maripaludis* (Met). These were completed with reactions from corresponding
177 manually curated genome-scale metabolic models (Islam et al., 2015; Richards et al., 2016),
178 resulting in 1193 reactions for Ace and 920 for Met (**Tables S1B and S1C**). Both the
179 acetogen and the methanogen metabolic networks contain RAFs. When all organic cofactors
180 are added to the food set, the maxRAFs contain 394 and 209 reactions for Ace and Met,
181 respectively, spanning major KEGG functional categories (**Figure 3; Tables S2 and S3,**
182 **Figures S2 and S3**).



183

184 **Figure 3. Autocatalytic networks point to an early autotrophic metabolism.**

185 Number of reactions in each functional category for three maxRAFs and functional
 186 enrichment compared with the global O₂-independent prokaryotic network. Colors represents
 187 bins of corrected p -values (Fisher's exact test with Benjamini–Hochberg FDR multiple-
 188 testing correction). From bottom to top, maxRAF obtained for (sizes in brackets): global O₂-
 189 independent prokaryotic network, acetogen (Ace) and methanogen (Met). Categories are
 190 sorted according to the number of reactions in the first maxRAF, from smallest to largest;
 191 only categories where this maxRAF had more than 10 reactions are shown.

192

193

194 Carbon fixation and biosynthetic pathways are represented and amino acids biosynthesis is
195 highly enriched in all maxRAFs, recovering autotrophic components of early autocatalytic
196 metabolism. The addition of peptide catalysis increases the maxRAF sizes obtained with the
197 global anaerobic network, Met, and Ace by 93%, 47%, and 25% respectively (**Table S2**).

198 This indicates that adding protein catalysis expands cofactor-supported autocatalytic sets, but
199 does so to a much lesser degree in the metabolism of Met and Ace than it does in the global
200 O₂-independent prokaryotic network.

201

202 **LUCA's metabolism was autocatalytic and autotrophic**

203 The intersection of the Ace and Met maxRAFs should be more ancient than either. Three-
204 quarters of the (smaller) Met maxRAF overlap with the (larger) Ace maxRAF in a connected
205 network harboring 172 reactions and 175 metabolites (**Figures 4 and 5**; individual maxRAFs
206 from Ace and Met in **Figures S2 and S3**). Six metabolites are disconnected, meaning the
207 species interconvert them using different pathways; one example is that of glucose,
208 catabolism of which arose after LUCA (Schönheit et al., 2016). Highly connected food
209 metabolites in the primordial network (more than 13 edges) include H₂O, ATP, protons,
210 phosphate, CO₂, NAD⁺, pyruvate, ammonia, diphosphate, coenzyme A and AMP; highly
211 connected non-food metabolites (more than eight edges) include ADP, NADH, and other
212 pyridine dinucleotides, glyceraldehyde-3-phosphate, and acetyl-CoA (**Table S4**). The
213 network is able to produce six amino acids—asparagine, aspartate, alanine, glycine, cysteine,
214 and threonine—plus the two nucleosides UTP and CTP. Cytochromes and quinones do not
215 figure into the network.

216



217 **Figure 4. Core autocatalytic metabolism of the last universal common ancestor (LUCA).**

218
219 Intersection of the maxRAFs obtained with the networks of *Moorella thermoacetica* and

220 *Methanococcus maripaludis* with a food set with organic cofactors (only metabolic

221 interconversions are depicted; catalysis arcs are omitted for clarity). Six metabolites,

222 including D-glucose and L-alanine (bottom) are in the intersection but disconnected from the

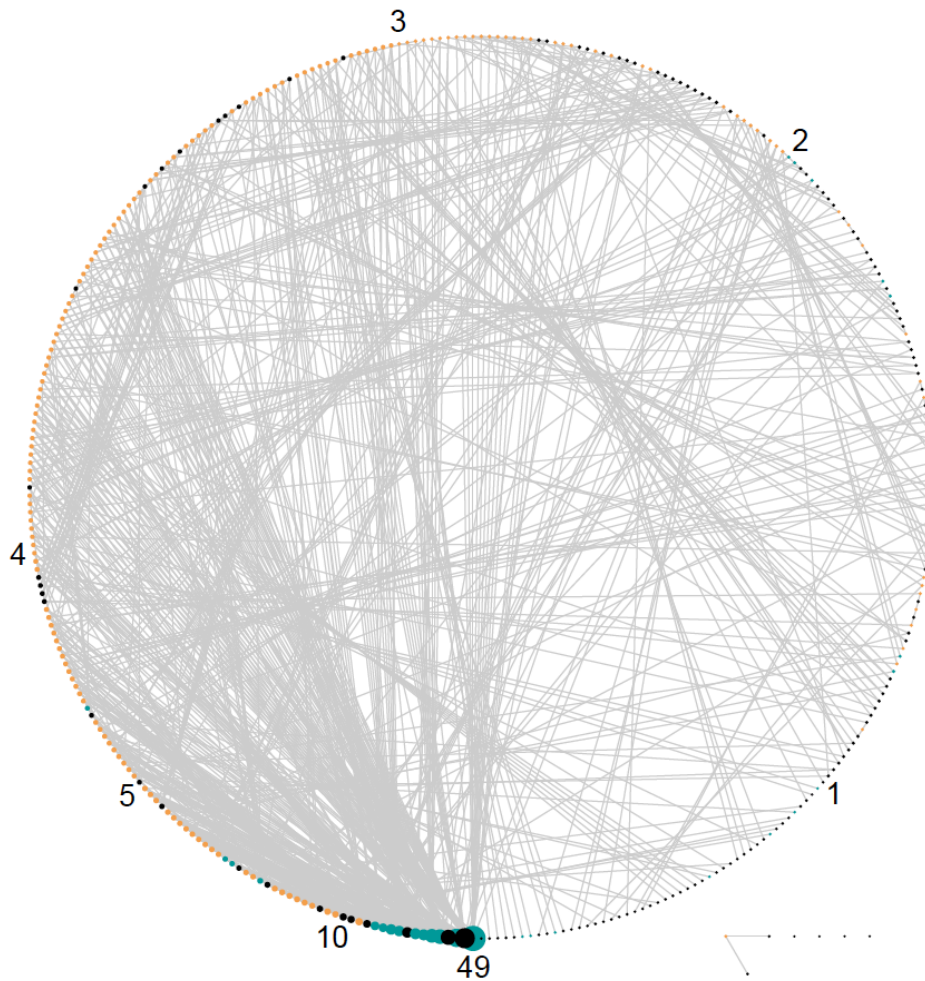
223 remaining network. The node size is scaled according to the degree, with food molecules

224 highlighted in green and relevant products in dark blue. ‘Acceptor’ and ‘Reduced Acceptor’

225 are abstract redox molecules as represented in KEGG metabolism.

226

227 A different look at the primordial network reveals a hierarchical and highly-connected
228 organization (**Figure 5**). The network is structured with a core half-moon, where the degree
229 varies from 49 to 4 (**Table S4**). Food molecules cluster in the most connected area, showing
230 the spark of autocatalytic metabolism by a handful of substrate molecules with degree higher
231 than 10.



232

233 **Figure 5. Circular bipartite representation of the autocatalytic metabolism in LUCA.**

234 Reactions (in orange) and metabolites (in green if food, grey for the rest) are represented as
235 nodes. Nodes are sorted according to degree clockwise starting from the bottom; numbers
236 show the degree at the respective position. ATP, the second most connected metabolite, can
237 be removed from the food set without impact, therefore here is represented in black.

238

239

240 **LUCA's metabolism is enriched in metal catalysis, ancient genes and autotrophic**
241 **functions**

242 In search of the distinct contributions for autocatalysis, we tested for enrichment in individual
243 catalysts, functions and ancient genes encoding for reactions in the primordial network. There
244 is a significant enrichment for metal and metal–sulfur cluster catalysis (**Figure 6A**), whereas
245 thiamine diphosphate (a carrier of C2 units in metabolism) is the only organic cofactor that is
246 significantly enriched in catalyzing the primordial network when compared with the global
247 network, even though several others are present and essential for the network to grow (**Figure**
248 **6B**). The primordial network is also enriched in reactions for amino acid biosynthesis, carbon
249 metabolism, and 2-oxocarboxylic acid metabolism when compared with the global network
250 (**Figure 6B**). Comparing reactions in the primordial network to those catalyzed by genes that
251 can be traced to LUCA by independent phylogenetic criteria (Weiss et al., 2016) uncovers
252 highly significant enrichment relative to both the global network and its maxRAF (**Figure**
253 **6C**). The maxRAF obtained within the primordial network contains 120 reactions and is
254 enriched in amino acid and carbon metabolism but produces cysteine as the sole amino acid,
255 which is noteworthy because cysteine is the hub of sulfur metabolism and also is the sole
256 ligand for incorporating Fe–S and Fe–Ni–S clusters in proteins (**Figure S4**).

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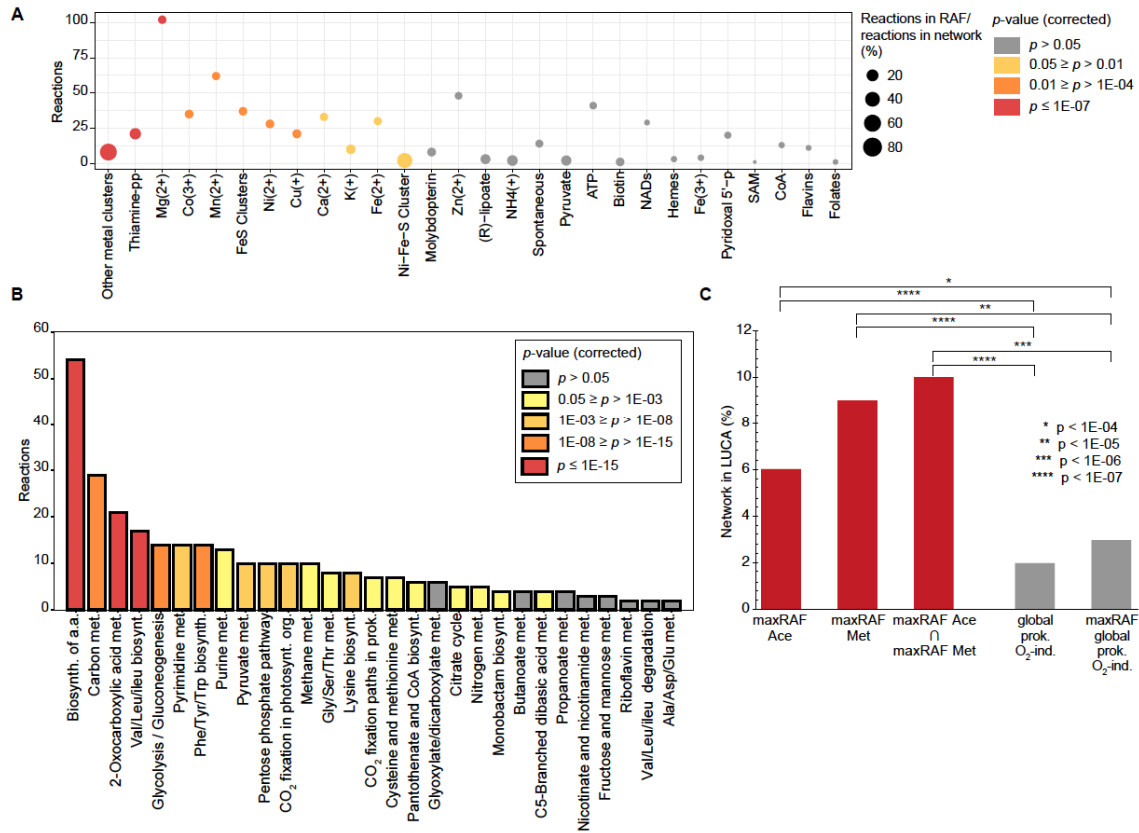


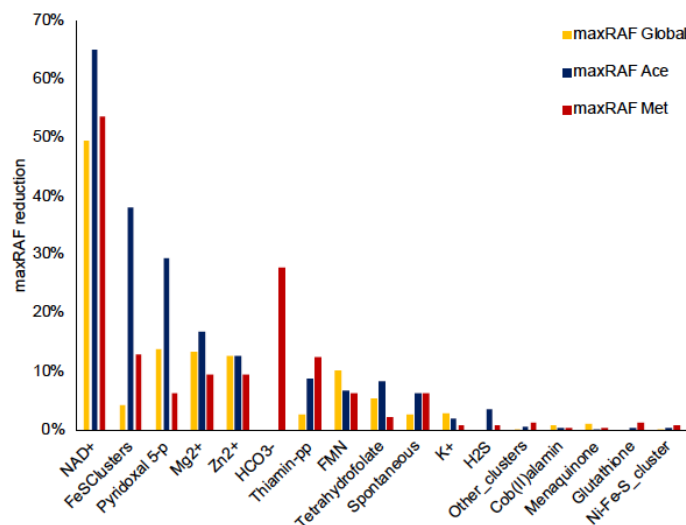
Figure 6. Properties of the core autocatalytic metabolism of the last universal common ancestor (LUCA).

(A) Enrichment of cofactors catalyzing the reactions in the overlapping network between the acetogen and methanogen maxRAFs compared with the global O₂-independent prokaryotic network. Circle size indicates the ratio between reactions in the intersection network and reactions in the global network; color indicates the corrected p -value (Fisher's exact test with Benjamini–Hochberg FDR correction). (B) Enrichment of KEGG pathways in the overlapping network compared with the global O₂-independent prokaryotic network. Color indicates bins of corrected p -values (Fisher's exact test with Benjamini–Hochberg FDR correction). (C) Proportion of metabolic networks predicted to be in LUCA (Weiss et al., 2016) and enrichment of the maxRAFs (red) compared with the global network and the maxRAF obtained with it (grey) (Fisher's exact test).

272 Autocatalysis before ATP and polymers

273 Crucial catalysts can be identified by removing them from the food set. NAD^+ is strongly
274 embedded in the RAF and its removal reduces the size of the maxRAF by ~50% (**Figure 7**).
275 Other compounds heavily impacting maxRAF size are Fe–S clusters, pyridoxal-5-phosphate
276 and divalent metals. Surprisingly, when we remove ATP from the food set of organic
277 cofactors, this has no impact on the size of the maxRAF, both for the individual networks
278 (**Figure 7**) and LUCA's network (**Figure 5**). Why does ATP removal have such a small effect
279 on RAFs? The simplest explanation is that ATP was not the primordial energetic currency
280 (Goldford et al., 2017). This points to the increasingly evident role of energy currencies other
281 than ATP in primordial metabolism, such as acyl phosphates (Martin and Russell, 2007),
282 thioesters (Semenov et al., 2016), and reduced ferredoxin (Herrmann et al., 2008, Müller et
283 al., 2018). Alternative energy currencies are particularly common in anaerobes (Müller et al.,
284 2018).

285



286

287 **Figure 7. Impact of removing single molecules from the food set with organic cofactors**
288 **on the size of maxRAFs.**

289 The impact is shown as the reduction in size of the maxRAF (percentage of the initial network
290 lost) when each molecule is removed from the food set with all organic cofactors, for the

291 global prokaryotic O₂-independent network (yellow), *Moorella thermoacetica* (dark blue) and
292 *Methanococcus maripaludis* (red).

293

294

295 RAFs provided with a food set containing catalysts can generate amino acids and bases
296 (**Figure 4**), but the converse is not true: adding amino acids and bases to the simplest food set,
297 which includes inorganic catalysts and CO₂ (**Table S2**), produces a miniscule 33-reaction
298 maxRAF (**Figure S5**). The maxRAF contains 47 metabolites, 27 of which are food molecules.
299 This indicates that autocatalytic networks embedded in microbial metabolism generated
300 amino acids and bases using small-molecule catalysis prior to the advent of nucleic acids or
301 peptide polymers.

302

303 **Discussion**

304 Autocatalytic networks are objects of molecular self-organization (Dyson, 1982; Eigen and
305 Schuster, 1977; Kauffman, 1986). Their salient property in the study of early biochemical
306 evolution is the capacity to grow in size and complexity. Compounds generated from the food
307 set become part of the network, hence autocatalytic networks can start small and grow, in
308 principle to a size approaching the complexity of metabolic networks of modern cells
309 (Hordijk et al., 2010), and very little catalysis by individual elements is required for
310 autocatalytic networks to emerge (Hordijk and Steel, 2004; Mossel and Steel, 2005).

311 Reflexively autocatalytic and food-generated networks—RAFs—are a particularly interesting
312 formalization of collectively autocatalytic sets, as they capture a property germane to life:
313 they require a constant supply of an environmentally provided food source in order to grow
314 (Hordijk and Steel, 2004). In that sense, RAFs reflect metabolic networks in real cells, in that
315 growth substrates are converted to end products, a proportion of which comprises the

316 substance of cells. But RAFs are far simpler than metabolism because they can start very
317 small.

318

319 RAFs have not been applied in the study of the evolution of chemical networks that led to the
320 metabolism of modern cells, themselves large natural autocatalytic networks. By embracing
321 the simple and robust premise that reactions catalyzed by simple molecules and inorganic
322 compounds preceded metabolic reactions catalyzed by enzymes (Sousa et al., 2015;
323 Stockbridge et al., 2010; White, 1976), we have retooled RAFs into an analytical instrument
324 to investigate the nature of metabolic evolution.

325

326 Our analyses start with the enzymatic and spontaneous reactions charted in modern
327 metabolism and use RAFs as a filter to uncover elements with self-organizational properties,
328 to address the nature of processes in the earliest phases of evolution, before the origin of
329 eukaryotes and before the appearance of oxygen. We find evidence for a role of autocatalytic
330 networks in the early evolution of metabolism. The largest RAF that we identified in the
331 whole prokaryotic anaerobic biochemical space has 1335 reactions and points to early
332 autotrophy. This RAF is larger than the genome size of the smallest free-living archaeon,
333 *Methanothermobacter ferredoxigenes* (Martínez-Cano et al., 2015). With a genome coding for 1,311
334 proteins and 50 RNA genes, *M. ferredoxigenes* lives from H₂ and CO₂ as carbon and energy sources
335 (the food set) and requires only inorganic, geochemical nutrients, no other cells for survival
336 (Anderson et al., 2010). H₂ and CO₂ were present in abundance on the early Earth and may
337 have given rise to the first metabolic pathways that brought forth the first archaeal and
338 bacteria cells (Goldford et al., 2017, Varma et al, 2018; Weiss et al., 2006). Our anaerobic
339 RAF is however smaller than the reaction network in the smallest genome of bacteria that live
340 from H₂ and CO₂, which is found in the acetogen *Thermoanaerobacter kivui*, encoding 2,378
341 proteins (Hess et al., 2014).

342

343 *M. fervidus* and *T. kivui* harbor primitive forms of methanogenesis and acetogenesis in that
344 they both lack cytochromes and quinones, suggesting that they represent energy metabolic
345 relics from the earliest phases of biochemical evolution on the primordial earth, before
346 anaerobic respiratory chains had evolved (Martin and Russell, 2007). To investigate this
347 aspect further, we examined the best annotated metabolic networks existing for H₂-CO₂
348 dependent archaea and bacteria, the methanogen *Methanococcus maripaludis* and the
349 acetogen *Moorella thermoacetica*. Remarkably, a food set containing only small abiogenic
350 molecules and a handful of organic cofactors generates sizeable RAFs in each of the
351 networks, with 209 and 394 reactions respectively. The inclusion of organic molecules as
352 catalysts in our food set is in line with a premise common to all scientific theories for the
353 origin of life, namely that the environment provided starting material from which metabolism
354 and life evolved.

355

356 RAFs uncover elements of metabolic evolution that go even further back in time before the
357 divergence of archaea and bacteria from the last universal common ancestor, LUCA. The
358 intersection of the RAFs of *M. maripaludis* and *M. thermoacetica* uncovers a fair amount in
359 common—a core, conserved autocatalytic network with 172 reactions that is enriched in
360 metal catalysis and carbon metal bonds (Martin, 2019) and also points both to early
361 autotrophy and to the genes of LUCA (Weiss et al., 2016). Our results also show that the
362 kickstart of autocatalysis in anaerobic metabolism does not require ATP. This is in
363 accordance with the use of alternative energetic currencies in anaerobic prokaryotes (Müller
364 et al., 2018) and recent findings that suggest that complexity in early metabolic reaction
365 systems could have emerged without phosphate (Goldford et al., 2017).

366

367 An important insight uncovered by RAFs is the observation that although a food set with
368 organic cofactors sparks a large autocatalytic network that generates amino acids and bases,
369 the opposite does not occur: adding amino acids and bases to the simplest food set (which
370 includes inorganic catalysts and CO₂) only produces a minute RAF with 33 reactions. This
371 result indicates that autocatalytic networks could generate amino acids and bases using
372 catalysts prior to the advent of complex nucleic acids or peptide polymers. This stands in
373 accordance with recent reports of amino acid synthesis catalyzed by native metals
374 (Muchowska et al., 2019), and also with the physiology of extant anaerobic autotrophs: amino
375 acids and bases are sequestered end-products of H₂ and CO₂ dependent metabolism, they are
376 polymerized to make the substance of cells.

377

378 RAFs as a tool to study metabolic evolution can serve as a guide for the identification and
379 construction of larger, biologically relevant autocatalytic reaction networks. The synthesis of
380 compounds characteristic of the metabolism of acetogens and methanogens, intermediates and
381 end products of the acetyl-CoA pathway and of the incomplete citric acid cycle from CO₂
382 using only the catalysis of native metals (Muchowska et al., 2019), as well as the
383 demonstrated catalytic power of organic cofactors without their enzymes including flavins
384 (Argueta et al., 2015), pyridoxal 5'-phosphate (Zabinski and Toney, 2001), SAM (Barrows
385 and Magee, 1982) and NAD (Betanzos-Lara et al., 2012) encourages the investigation of
386 more complex autocatalytic networks in laboratory reactors.

387

388 Our results are directly relevant to two deeply divided schools of thought concerning the
389 nature of chemical reactions at the origin of life: genetics first and metabolism first. The
390 genetics first school, or RNA world, holds that the origin of RNA molecules marked the
391 origin of life-like processes, and that RNA both self-replicated and possessed catalytic
392 abilities that led to the emergence of biochemical reactions (Orgel, 2008; Patel et al., 2015).

393 In that view, the origin of the bases that drove that process forward is decoupled from
394 biochemical processes that are germane to modern cellular metabolism. The metabolism-first
395 school holds that spontaneous (exergonic) chemical reactions preceded reactions catalyzed by
396 genetic material, and that those exergonic reactions continuously gave rise to substrate-
397 product relationships (Martin and Russell, 2007; Morowitz et al., 2000). From such reactions,
398 more complex interaction networks with autocatalytic properties arose (Kauffman, 2011;
399 Smith and Morowitz, 2004), in which elements of the set intervened in reactions of the set,
400 providing structure and direction to product accumulation. Our results show that in RAFs of
401 anaerobic metabolism, nucleoside-related cofactors play a central role, albeit these have
402 functional moieties that do not occur in RNA as it catalyzes protein synthesis. More
403 importantly, our findings indicate that RNA could arise from metabolism, and the nature of
404 the products accumulated in RAFs will include nucleic acids. In other words, RAFs applied to
405 ancient autotrophic metabolism reveal a vector of autopoietic genesis that detects RNA
406 emerging from metabolism rather than vice versa.

407

408 **Materials and Methods**

409 **Catalysis-annotated metabolic networks**

410 All the reactions and the EC numbers they are linked to were retrieved from KEGG (Kanehisa
411 et al., 2017), along with their corresponding taxonomic annotations using the KEGG REST
412 API (<https://www.kegg.jp/kegg/rest/keggapi.html>, accessed February 2018). The EC–reaction
413 pairs were filtered by excluding reactions annotated only in eukaryotes. The corresponding
414 chemical equations were then parsed to discard reactions involving molecular oxygen.
415 Spontaneous reactions were parsed out of KEGG and added to the network with a fictional
416 catalyst named “Spontaneous”. Reactions catalyzed by enzymes that are not spontaneous and
417 the enzymes of which do not use any cofactors were assigned the catalyst “Peptide”.

418 Reactions that equate synonymous cofactors were added with the generic catalyst “Pooling”.

419 Extensive curation was performed regarding catalysis rules, reaction reversibility, and amino

420 acid production. The reversibility of reactions was parsed out of KGML files for KEGG

421 pathways and manually–curated. The resulting set of reactions was then integrated with

422 cofactor information from Uniprot (The Uniprot Consortium, 2018) through the

423 corresponding EC numbers. Eighty-one unique cofactors were retrieved from Uniprot, which

424 translated to 48 KEGG compounds or pools of catalytically equivalent cofactors linked to

425 KEGG reactions through the EC numbers. Cofactors directly participating in reactions

426 (NADs, ATP, SAM, CoA, Cobalamins, Folates, Flavins and Quinones) were extracted from

427 the reaction stoichiometry if not assigned as cofactors in Uniprot. Of all EC numbers searched

428 in Uniprot, 34% had at least one associated cofactor, 579 of which were EC numbers that

429 involved more than one cofactor when parsed in a Boolean manner. All rules were added to

430 the network as additional parameters. The subsets for Met and Ace were obtained by crossing

431 the genomic annotation of *Moorella thermoacetica* and *Methanococcus maripaludis* in KEGG

432 with the previously built network, and with the addition of missing reactions that were present

433 in corresponding manually–curated models (Islam et al., 2015, Richards et al., 2016). The

434 pipeline for the full procedure is shown in **Figure S1**.

435

436 **Detection of maxRAFs**

437 All networks described above were tested for whether they contained maxRAFs with different

438 food sets, which are described in the main text and available in **Table S2**. The fictional

439 catalysts “Spontaneous” and “Pooling” were added in all tests, allowing for spontaneous

440 reactions to always occur and synonymous cofactors to be equated. Pooling reactions that

441 were part of the maxRAF were not accounted for in maxRAF sizes.

442

443

444 **RAF sets**

445 We define a *chemical reaction system* (CRS) as a tuple $Q = \{X, R, C, F\}$, where:

- 446 • $X = \{x_1, x_2, \dots, x_n\}$ is a set of molecule types.
- 447 • $R = \{r_1, r_2, \dots, r_m\}$ is a set of reactions. A reaction r is an ordered pair $r = (A, B)$ where
448 $A, B \subset X$. The (multi)set $A = \{a_1, \dots, a_s\}$ indicates the reactants and the (multi)set
449 $B = \{b_1, \dots, b_t\}$ indicates the products.
- 450 • $C \subseteq X \times R$ is a set of catalysis assignments. A catalysis assignment is a pair (x, r) with
451 $x \in X$ and $r \in R$, denoting that molecule type x can catalyse reaction r .
- 452 • $F \subset X$ is a food set (i.e., molecule types that can be assumed to be available from the
453 environment).

454 Given a CRS Q , a subset R' of R , and a subset X' of X , we define the *closure* of X' relative to
455 R' , denoted $cl_{R'}(X')$, to be the (unique) minimal subset W of X that contains X' and that
456 satisfies the condition that, for each reaction $r = (A, B)$ in R' ,

$$A \subseteq X' \cup W \Rightarrow B \subseteq W.$$

457 Informally, $cl_{R'}(X')$ is X' together with all molecules that can be constructed from X' by the
458 repeated application of reactions from R' .

459 Given a CRS $Q = \{X, R, C, F\}$ and a subset R' of R , R' is a *RAF set* if for each $r = (A, B) \in$
460 R'

- 461 1. (Reflexive Autocatalysis): $\exists x \in cl_{R'}(F): (x, r) \in C$, and
462 2. (Food-generated): $A \subseteq cl_{R'}(F)$.

463 In other words, a subset of reactions R' is a RAF set if, for each of its reactions, at least one
464 catalyst and all the reactants are in the closure of the food set relative to R' (Hordijk and Steel,
465 2004).

466

467

468 **RAF algorithms**

469 Given a CRS $Q = \{X, R, C, F\}$, an efficient (polynomial-time) algorithm exists for deciding
470 whether Q contains a RAF set or not. It is presented formally in Algorithm 1.

471

472 **Algorithm 1** RAF (X, R, C, F)

```
473    $R' = R$ 
474    $change = true$ 
475   while ( $change$ ) do
476      $change = false$ 
477     Compute  $cl_{R'}(F)$ 
478     for all ( $r = (A, B) \in R'$ ) do
479       if ( $\nexists x \in cl_{R'}(F) : (x, r) \in C \vee A \not\subseteq cl_{R'}(F)$ ) then
480          $R' = R' \setminus \{r\}$ 
481          $change = true$ 
482       end if
483     end for
484   end while
485   Return  $R'$ 
```

486

487 In plain words, starting with the full set of reactions R , the algorithm repeatedly calculates the
488 closure of the food set relative to the current reaction set R' and then removes all reactions
489 from R' that have none of their catalysts or not all of their reactants in this closure. This is
490 repeated until no more reactions can be removed. If, upon termination of the algorithm, R' is
491 non-empty, then R' is the unique *maximal* RAF set (maxRAF) contained in Q (i.e., a RAF that
492 contains every other RAF in Q as a subset) (Hordijk and Steel, 2004). If R' is empty, then Q
493 does not contain a RAF set.

494 Computing the closure of the food set relative to the current reaction set R' is computationally
495 the most expensive step in the RAF algorithm. It is presented formally in Algorithm 2. This
496 closure computation algorithm, introduced in Hordijk and Steel (2004), is equivalent to the
497 “network expansion” algorithm (Ebenhöh et al., 2004) used in Goldford et al. (2017).

498

499 **Algorithm 2** ComputeClosure (F, R')

```
500    $W = F$ 
501    $change = true$ 
502   while ( $change$ ) do
503      $change = false$ 
504     for all ( $r = (A, B) \in R'$ ) do
505       if ( $A \subseteq W \wedge B \not\subseteq W$ ) then
506          $W = W \cup B$ 
507          $change = true$ 
508       end if
509     end for
510   end while
511   Return  $W$ 
```

512

513 A naive computational complexity analysis of the RAF algorithm gives a worst-case running
514 time of $O(|X||R|^3)$. However, with some additional book-keeping (such as keeping track of
515 all reactions that each molecule is involved in), this can be reduced. In fact, the average
516 running time on a simple polymer-based model of CRSs turns out to be sub-quadratic
517 (Hordijk and Steel, 2004).

518

519 **LUCA enrichment analysis**

520 The genetic families identified in Weiss et al. (2016) were mapped to KEGG orthologues, the
521 corresponding EC numbers were retrieved and the reactions performed by these were listed
522 and compared with the lists of reactions comprising the different networks, namely the global
523 O_2 -independent prokaryotic network; the maxRAF obtained with this network; maxRAFs
524 obtained with the Ace and Met subsets; and the intersection of these.

525

526 **Statistical Analysis**

527 Fisher's exact tests with Benjamini–Hochberg multiple test corrections were performed for
528 pathway and cofactor enrichment analysis (Figures 3, 6A-B), and significance was considered
529 for corrected p -values smaller than 0.05. A Fisher test was performed for enrichment in

530 LUCA genes (Figure 6C) and significance was considered for p -values smaller than 0.0001.

531 All statistical analysis were performed in Python ver. 3.6.6 with the package `scipy.stats`.

532 Network properties were calculated and visualizations were produced with Cytoscape

533 (Shannon, 2003) ver. 3.7.1.

534

535 **Software availability**

536 A custom-made implementation of the maxRAF algorithm was used for the analysis in this

537 paper and is available at <https://www.canterbury.ac.nz/engineering/schools/mathematics->

538 [statistics/research/bio/downloads/raf/](https://www.canterbury.ac.nz/engineering/schools/mathematics-statistics/research/bio/downloads/raf/). An example of an input file (global prokaryotic O₂-

539 independent network, food set with all small molecules, abiotic carbon and organic cofactors)

540 is given in **Data S1**. A more general-purpose and interactive RAF analyzer can be found

541 online at <http://www.math.canterbury.ac.nz/bio/RAF/>, including several more examples and

542 explanations.

543

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549

550 **Author contributions**

551 JCX collected and integrated data from databases, curated models, and literature. JCX, MS,

552 SK and WFM designed the project. WH and MS wrote the pseudocode and algorithm for

553 detection of maxRAFs and WH performed maxRAF identification. JCX and WFM wrote the

554 first manuscript draft. JCX, WH, SK, MS, and WFM contributed in data interpretation and
555 writing the final manuscript.

556

557 **Supplementary Information Titles and Legends**

558 **Figure S1. Pipeline of reconstructing catalysis-annotated metabolic networks.** Steps in
559 grey include metabolic data only, steps in brown include catalysis rules, and steps in greens
560 represent the inclusion of curated data from metabolic models of *Moorella thermoacetica* and
561 *Methanococcus maripaludis*.

562 **Figure S2. MaxRAF obtained with the network of *Moorella thermoacetica*.** Node size is
563 scaled according to the degree, with food molecules highlighted in green and relevant
564 products in dark blue (only metabolic interconversions are depicted; catalysis arcs are omitted
565 for clarity). ‘Acceptor’ and ‘Reduced Acceptor’ are abstract redox molecules as represented
566 in KEGG metabolism.

567 **Figure S3. MaxRAF obtained with the network of *Methanococcus maripaludis*.** Node size
568 is scaled according to the degree, with food molecules highlighted in green and relevant
569 products in dark blue (only metabolic interconversions are depicted; catalysis arcs are omitted
570 for clarity). ‘Acceptor’ and ‘Reduced Acceptor’ are abstract redox molecules as represented
571 in KEGG metabolism.

572 **Figure S4. MaxRAF obtained with the intersection of the networks of *Methanococcus***
573 ***maripaludis* and *Moorella thermoacetica*.** Node size is scaled according to the degree, with
574 food molecules highlighted in green and relevant products in dark blue (only metabolic
575 interconversions are depicted; catalysis arcs are omitted for clarity). ‘Acceptor’ and ‘Reduced
576 Acceptor’ are abstract redox molecules as represented in KEGG metabolism.

577 **Figure S5. MaxRAF obtained with amino acids and bases.** The network represents the
578 maxRAF obtained with the full prokaryote O₂-independent network with inorganic catalysts,

579 abiotic compounds, all amino acids and bases but no organic cofactors added to the food set
580 (only metabolic interconversions are depicted; catalysis arcs are omitted for clarity). Node
581 size is scaled according to the degree, with food molecules highlighted in green. ‘Acceptor’
582 and ‘Reduced Acceptor’ are abstract redox molecules as represented in KEGG metabolism.
583 **Table S1. Metabolic networks annotated with catalysis rules. (A)** Prokaryotic, O₂-
584 independent global metabolic network **(B)** subset network of *Moorella thermoacetica* **(C)**
585 subset network of *Methanococcus maripaludis*.

586 **Table S2. Composition of Food Sets used in predictions of maxRAFs in different**
587 **metabolic networks and resulting maxRAF sizes.**

588 **Table S3. Lists of reactions in all maxRAFs predicted for all networks in all food sets.**

589 **Table S4. Connectivity of metabolites in LUCA’s maxRAF.**

590 **Data S1. Input file with the global prokaryotic O₂-independent network used to run the**
591 **maxRAF algorithm.** Food set with all small molecules, abiotic carbon and organic cofactors.

592

593

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