tual quality in the brain with a machine learning process to examine the impact of the first processing stages on the scent quality prediction. Eight hundred and thirty-six odorants were used to train a Naïve-Bayes classifier, which is well suited for classification without the need to optimize additional free variables. This modeling step revealed that the previous decorrelation step can significantly improve the accuracy of odorant classification compared with using the Naïve-Bayes classifier with the initial chemical descriptors but without the decorrelation procedure. Moreover, the proposed method was shown to be capable of dimensionality reduction and is more robust than principal component analysis.

Interestingly, it seems that the the application of this framework is not just limited to olfactory systems: it can also be used for virtual screening of pharmaceutical compound databases. The same processing scheme was used for pharmacologically active substances instead of odorants, and the 'perceptual qualities' of odorant substances were replaced by the annotated activity of the molecules at pharmaceutical targets. The overall performance of the methods was, in this case, even better for the pharmaceutical dataset than for the odorants, although the advantage of the virtual response patterns compared to principal component analysis was less obvious than in the odorant dataset.

Perspectives and conclusions

The approach by Schmuker and Schneider presents a novel and extremely promising way to increase the prediction performance for odorant data by using virtual receptors and functional inhibition. Moreover, the application of this processing method to other data that are difficult to classify showed that weak decorrelation has advantages over principal component analysis. Looking into the future, this decorrelation technique might find applications for low-dimensional mapping of complex data, for example in modeling structure–activity relationships and virtual compound screening.

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Letters

Do biofuels from microalgae beat biofuels from terrestrial plants?

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The best way to displace fossil fuels is much debated. Chisti [1] has argued that in displacing fossil fuels, microalgal biodiesel outperforms biodiesel and bioethanol from terrestrial plants because microalgal biofuel yields ha^{-1} can be larger. However, Chisti did not consider fossil fuel inputs during the biofuel life cycle. Fossil fuels are currently used for building the facilities (bioreactor, pond) and for operational activities such as supplying nutrients, maintenance, mixing, the collection of microalgae and biomass processing.

Two previous studies have addressed fossil fuel inputs into the life cycle of biofuels from microalgae that can be commercially grown in open ponds. Sawayama *et al.* [2] studied operational fossil fuel inputs into growing and processing *Dunaliella tertiolitica* to supply microalgal oil. Energy inputs exceeded energy output by 56% when microalgal yield was 15 $Mg\,ha^{-1}\,year^{-1}$ (dry weight). Hirano *et al.* [3] investigated *Spirulina* production and its subsequent processing for supplying methanol. The

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Table 1. Net energy yields in GJ ha^{-1} $year^{-1}$ for biofuels and photovoltaic modules

Solar radiation conversion by:	Location	Product	Net energy yield in GJ ha^{-1} $year^{-1}$
Sugarcane [4]	Brazil	Ethanol	161–175
Oil palm [5,6]	Malaysia	Palm oil	142–180
Spirulina, as assumed by Hirano [3]	Not specified	Methanol	127
Dunaliella tertioltica, as studied by Sawayama *et al.* [2]	Not specified	Oil	Negative
Biofuels from micoalgae grown in bioreactors [9]	Not specified	Variable	Negative
Photovoltaic modules (multicrystalline Si) [10–12]	Brazil	Electricity	76×10^2–87×10^2

assumed biomass yield was 110 Mg ha^{-1} $year^{-1}$ (dry weight), and the conversion efficiency of biomass to methanol was assumed to be 64%. When the fossil fuel inputs into the building and operation of the facility were considered, the energy output exceeded the life cycle fossil fuel input by 10% [3].

Empirical data show that, in practice, sugarcane and oil palm yield less biomass than the 110 Mg ha^{-1} $year^{-1}$ assumed for *Spirulina* by Hirano *et al.* [3], but these terrestrial plants are characterized by lower fossil fuel inputs into the biofuel life cycle for a specified amount of biofuel energy [4–6] than in the case of the microalgal biofuels studies mentioned before [2,3]. To assess the potential for fossil fuel displacement, net energy yields ha^{-1} $year^{-1}$ for biofuels can be calculated by subtracting the input of fossil fuels from the output of biofuel. Using a lower heating value for ethanol of 26.4 MJ kg^{-1}, Macedo *et al.* [4] calculate a net energy yield ha^{-1} $year^{-1}$ of 161–175 GJ for the current ethanol production from sugarcane in Brazil. In the case of Malaysian palm oil, depending on the use of varying estimates for fossil fuel inputs [5,6], a net energy yield in the range of 142–180 GJ ha^{-1} $year^{-1}$ can be estimated. For methanol production as discussed by Hirano *et al.* [3] and assuming a lower heating value for methanol of 19.9 MJ kg^{-1} [7], a net energy yield ha^{-1} $year^{-1}$ of 127 GJ can be calculated, which is lower than the values obtained for the two terrestrial biofuels considered here.

Moreover, it remains to be seen whether an annual yield of 110 Mg biomass ha^{-1}, which has been assumed by Hirano *et al.* [3], could actually be achieved in practice in open ponds. These ponds are characterized by extreme conditions, which are necessary for the elimination of competing algae and grazers but are not conducive to maximizing biomass yields [8]. Indeed, the yield assumed by Hirano *et al.* [3] is far beyond the actual values in the range of 10–30 Mg ha^{-1} $year^{-1}$ that are achieved for *Spirulina* production in commercial facilities [8].

An alternative possibility to open ponds is the production of microalgal biodiesel in bioreactors. This allows the growth of a much wider variety of microalgae under conditions that are more suitable to obtaining maximized yields. However, growing algae in bioreactors requires fossil fuels for the building of these bioreactors and for their operational activities. Wijffels [9] has estimated the input of fossil fuels for state-of-the-art bioreactors and concluded that flat panel bioreactors could result in a negative energy balance, and this could be even more pronounced for tubular bioreactors.

From the studies available so far that have considered life cycle fossil fuel inputs, it could be concluded that the microalgal biofuels studied might not be able to beat biofuels from terrestrial plants with respect to net energy yield ha^{-1} $year^{-1}$, and thus might also not be able to beat biofuels from terrestrial plants in displacing fossil fuels.

Current technologies that are able to outperform biofuels from terrestrial plants with respect to net energy yield ha^{-1} instead rely on the direct conversion of solar energy into usable energy, such as electricity. This is illustrated by Table 1, which compares net energy yields ha^{-1} $year^{-1}$ obtained from different biofuels with that of multicrystalline Si photovoltaic modules. Regarding the energy yield of such modules, it is assumed that the solar irradiation ha^{-1} $year^{-1}$ is 6.94×10^4 GJ, which is an average for Brazil [10], and that the overall energy efficiency of the modules is 11–12.6% [11,12]. From Table 1, one can conclude that, whereas the microalgal biofuels discussed by Sawayama *et al.* [2], Hirano *et al.* [3] and Wijffels [9] might not be able to beat biofuels from terrestrial plants with respect to net energy yield ha^{-1} $year^{-1}$, multicrystalline Si photovoltaic modules beat these biofuels by more than one order of magnitude.

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